Engineering Judgment Calls for AGI: Binary Decisions Under Uncertainty, Safe Defaults, and No-Audit Catastrophe Governance

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Humans use the phrase “judgment call” when facts are incomplete, time is short, and the choice depends on tradeoffs that cannot be resolved by calculation alone. In the AGI era, these moments will not disappear; they will become more frequent, faster, and more consequential. Some judgment calls are advisory and reversible, but others are immediate yes-or-no decisions where a single mistake can cascade into irreversible harm. In those “no-audit” situations, the usual comfort of after-action review fails: there may be nothing left to investigate, and no opportunity to learn from the error. This paper argues that the right question is not whether AGI can make perfect judgment calls, but how to design systems so that unavoidable uncertainty is handled safely. We develop a framework that separates factual inference from normative authority, makes uncertainty operational through thresholds and safe defaults, and replaces brittle “oracle” behavior with layered gates, reversible first moves, and hard constraints. We propose domain-sensitive error asymmetries, escalation protocols, and governance patterns that prevent any single inference from becoming a catastrophic final act. The goal is practical: transform judgment from vibes into architecture.

Keywords: artificial general intelligence, judgment calls, decision-making under uncertainty, binary decisions, confidence thresholds, safe defaults, irreversible risk, catastrophe prevention, human oversight, escalation protocols, robust decision theory, safety envelopes, multi-agent gating, no-audit scenarios, auditability, governance, risk management.

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1. Introduction: Why “Judgment Calls” Don’t Go Away

The phrase “judgment call” is a compact confession. It admits that the world has not supplied enough information to turn a choice into a proof, yet action is still required. It also admits that choices are never only about facts. They are about priorities: whose risk counts, which harms are tolerable, what is reversible, what is sacred, what must not be gambled. Even in domains saturated with data, judgment calls persist because they arise from structural features of reality: uncertainty, time pressure, conflict between goods, and the asymmetry of harm. The arrival of AGI does not abolish those features. Instead, it raises the stakes and compresses the timeline.

A central claim of this paper is that the AGI era should force a shift in how we talk about judgment. It is tempting to imagine that better prediction eliminates judgment, and that enough intelligence converts “hard calls” into “obvious answers.” But the hardest calls are hard precisely because they contain a normative core: they require authorization, not merely inference. In high-consequence settings, the question becomes less “Can the system decide?” and more “Who gave it permission to decide?” and “What design prevents one wrong decision from becoming irreversible?”

This introduction frames judgment calls as an engineering and governance problem, not a psychological mystery. The objective is not to replace human judgment with machine judgment, but to build systems that act safely when judgment is demanded by circumstance. That means separating what is known from what is permitted, treating uncertainty as operational, and designing defaults that resist catastrophe even when the model is wrong.

1.1 What humans mean by a judgment call

In everyday language, a judgment call is not merely a difficult decision. It is a decision with at least four traits.

First, the evidence is incomplete or contradictory. The person deciding senses that more information could change the conclusion, but there is no time to obtain it or no way to obtain it at all. Second, the outcome is uncertain. Even if the present facts were perfectly known, the causal chain from action to outcome is noisy, complex, or adversarial. Third, the decision involves a tradeoff among values. It is not only “What will happen?” but “Which cost is acceptable?” and “Who bears it?” Fourth, there is an implied responsibility: if the decision goes badly, someone will be blamed, whether fairly or not.

This is why “judgment call” functions socially as both shield and warning. It is a shield because it signals the absence of certainty, and a warning because it signals the presence of risk. Humans also use the phrase to mark the boundary between algorithmic rule-following and discretionary choice. A referee makes a judgment call when the rulebook underdetermines the moment. A

physician makes a judgment call when the guideline does not fit the patient. A commander makes a judgment call when intelligence is ambiguous but the window for action is closing.

Importantly, humans often make judgment calls through tacit heuristics that evolved for survival and social coordination: caution under unknown threat, empathy for visible suffering, loyalty to in-group norms, and deference to authority. Those heuristics can be wise, and they can be disastrous. They are sensitive to framing, fatigue, fear, ideology, and momentum. Yet even when humans are wrong, their judgment is embedded in accountability structures—courts, professional boards, elections, the moral judgment of peers. That accountability is imperfect, but it signals something crucial: judgment is not only cognition; it is legitimacy.

The AGI era forces us to formalize what "judgment" means when the decider is not a person. If an AGI outputs "yes" in a gray zone, was that a factual inference, a policy decision, or an unauthorized value substitution? For human agents, these categories blur. For machine agents, blurring them is a hazard.

1.2 Why AGI makes the problem sharper: speed, scale, delegation

AGI changes the judgment landscape in three reinforcing ways.

Speed: Machine decisions compress time. Many systems already operate at machine time—trading, cybersecurity response, industrial control. AGI extends that capability into broader domains and more ambiguous contexts. As speed increases, the tolerance for deliberation drops, and the default temptation becomes automation: "Let the system decide." But the faster the loop, the more dangerous it is to treat inference as authority. A decision that might have been debated for minutes by humans can become a millisecond output that triggers irreversible processes.

Scale: Machine decisions replicate. Human judgment calls are limited by attention and fatigue. A single human can make only so many high-quality discretionary decisions per day. An AGI can make millions, and the error mode changes accordingly. Instead of occasional mistakes, the risk becomes systematic error: the same miscalibration applied everywhere, instantly. Scale also means that small biases, slight overconfidence, or mis-specified objectives are amplified into population-level consequences. If judgment is wrong at scale, it becomes policy by accident.

Delegation: The most profound change is that organizations will delegate not only computation but discretion. They will ask the system to decide what to prioritize, what to ignore, whom to flag, whom to trust, when to escalate, when to shut down. Delegation happens because it is convenient, because it lowers staffing burdens, because it reduces latency, because it appears "objective," and because it can be hidden inside pipelines. Yet delegation shifts moral weight. When discretion is delegated, responsibility becomes ambiguous: was the harm caused by the designers, the operators, the policymakers, or the model?

AGI therefore sharpens judgment calls in two ways at once. It increases the number and speed of judgment-like decisions, and it threatens to dissolve the accountability structures that give judgment legitimacy. If no one can explain, authorize, or meaningfully review a decision, then the system is not exercising judgment. It is exercising power without ownership.

The correct response is not to pretend delegation won't happen. It will. The correct response is to design delegation so that it is bounded: the system can advise broadly, act within constraints, and escalate to human authority when the decision is fundamentally normative or irreversible.

1.3 The special case: immediate yes/no decisions under uncertainty

Judgment calls become most morally charged when they collapse into a binary: yes or no, now or never. Binary decisions feel clean, but they are often the most dangerous because they hide complexity behind a single bit.

Immediate yes/no decisions have three distinctive properties.

First, they usually occur under time pressure where information gathering is limited. The decider cannot "wait for clarity." Second, the decision is often entangled with irreversible outcomes: a lethal act, a system shutdown, an evacuation order, a sudden financial liquidation, a denial of medical intervention. Third, binary decisions force a choice between error types: false positives and false negatives. If you say "yes" when it should have been "no," you may cause harm by acting. If you say "no" when it should have been "yes," you may cause harm by failing to act.

Humans handle this with a mix of training, doctrine, and learned caution. But human performance is inconsistent. Humans panic, freeze, over-trust intuition, or over-trust authority. Machines introduce a different failure profile. An AGI can be fast, consistent, and often correct—yet catastrophically wrong in specific, structured ways: distribution shift, adversarial manipulation, spurious correlations, miscalibrated confidence, or misaligned objective proxies.

Binary immediacy is where the design question becomes stark: what do we want the default posture to be when the system is uncertain? In some domains, the morally acceptable bias is toward "no" unless extremely confident, because false positives are intolerable (for example, use-of-force). In other domains, the acceptable bias is toward "yes" for reversible stabilizing actions, because false negatives are lethal (for example, certain emergency interventions). In both cases, the choice of bias is not a statistical detail. It is a moral and legal decision that must be made explicitly, prior to the moment of action.

A well-designed AGI system therefore does not treat "yes/no now" as a single monolithic output. It treats it as the endpoint of a pipeline with thresholds, safe defaults, escalation

triggers, and bounded actuation. When the output must be binary, the surrounding architecture must carry the nuance that the bit cannot.

1.4 The “no-audit” condition and why it changes the design goal

Many safety programs assume the possibility of learning from failure. Aviation improves because accidents are investigated. Medicine improves because outcomes can be reviewed. Industrial processes improve because near-misses are analyzed. This logic collapses in “no-audit” scenarios: cases where a wrong decision leaves no meaningful evidence, no surviving system, or no opportunity for review. Sometimes this is literal destruction. Sometimes it is social or geopolitical irreversibility. Sometimes it is cascading failure in tightly coupled systems where the original trigger cannot be reconstructed.

When there is nothing left to audit, post-mortem learning cannot be the primary safety strategy. The design goal changes from “detect and correct errors” to “prevent irreversible actions from being triggered by a single fallible inference.” In other words, the system must be built so that certain classes of failure are structurally difficult, not merely statistically rare.

This is why the paper introduces the principle: no single inference should be able to end the world. In practical terms, that means refusing single-point agency for catastrophic actions. It means gates, redundancy, and hard constraints. It means reversible-first action design. It means circuit breakers that activate when conditions are unfamiliar. It means a clear boundary between recommendation and execution. And it means explicit human authorization for actions that cross moral red lines or entail irreversible harm at scale.

No-audit conditions also expose a deeper truth about “judgment” itself. In ordinary settings, judgment can be defended by intent, by good faith, by competence, by the reasonableness of the decision under uncertainty. But in no-audit settings, those defenses become meaningless if the outcome is annihilation. The moral standard becomes closer to stewardship than to cleverness: do not build systems where the margin for error is smaller than the world can afford.

So the introduction ends with a reframing. The goal is not to produce an AGI that makes human-like judgment calls. The goal is to engineer decision architectures in which uncertainty is acknowledged, authority is explicit, catastrophic pathways are gated, and the default posture is safe even when the model is wrong. In this framing, “judgment” is not a mysterious virtue inside the machine. It is a property of the whole sociotechnical system: the rules, the constraints, the escalation protocols, and the legitimacy of who is allowed to decide.

2. From Intuition to Structure: Defining the Decision Class

The phrase “judgment call” is useful precisely because it bundles several distinct ingredients into one everyday label. But that bundling is a liability when we design AGI decision systems. If we do not separate the ingredients, we cannot decide what should be automated, what must be gated, what should be escalated, and what must never be executed by a system acting alone.

This section turns the intuitive notion of a judgment call into a structured decision class. The aim is not to replace human discretion with mathematical formalism, but to specify the minimum structure required for safety: what kinds of uncertainty are present, what kinds of harms are on the table, what kinds of values are being traded, and what kinds of actions are reversible. Once those dimensions are explicit, we can define rules that are stable under pressure: thresholds, defaults, escalation triggers, and permission boundaries.

A simple way to state the problem is this: judgment calls are decisions made when the mapping from observation to action is underdetermined by facts alone. Under those conditions, a system must avoid two opposite errors. One error is paralysis: refusing to act when action is morally required. The other is unauthorized action: acting as if a value conflict were a factual certainty. A workable framework must give the system a disciplined middle path: act when authorized, refrain when uncertain, escalate when values conflict, and prioritize reversible moves when stakes are high.

2.1 Incomplete evidence, uncertain outcomes, and value-laden tradeoffs

A decision becomes a judgment call when three kinds of indeterminacy converge.

First is evidential indeterminacy: the system does not possess the information needed to uniquely determine what is happening. This may be because the world is occluded, sensors are noisy, reports are contradictory, adversaries are deceptive, or the situation is novel relative to prior data. Importantly, “incomplete evidence” is not synonymous with “low information.” A system can have massive data streams and still lack the crucial discriminating variable that would settle the case. More data can even worsen the situation by increasing spurious correlations and the temptation to treat pattern detection as truth.

Second is outcome indeterminacy: even if the present were perfectly understood, the future remains probabilistic. Complex systems exhibit nonlinear response, hidden feedback loops, and sensitive dependence on initial conditions. In strategic environments, outcomes depend on other agents who adapt. In human environments, outcomes depend on trust, legitimacy, and social meaning, which are not fully predictable in any strict sense. This kind of uncertainty is not a temporary gap awaiting better models; it is a permanent feature of open systems.

Third is normative indeterminacy: the decision cannot be justified by prediction alone because it involves competing goods. Here “value-laden” does not mean ideological. It means that the choice distributes risk and benefit across persons, time horizons, and moral categories. For example, “maximize throughput” conflicts with “minimize error” when errors harm real people. “Act quickly” conflicts with “avoid collateral damage.” “Prevent rare catastrophe” conflicts with “avoid constant false alarms and unjust restrictions.” These are not computational problems; they are governance problems.

When all three converge, a crucial design question appears: does the system have legitimate authority to trade those values? If the values have been explicitly authorized by the relevant authority, then the system’s job is to implement them under uncertainty. If the values have not been authorized, then the system must not silently substitute its own. A system that outputs a decisive recommendation without revealing the value tradeoff is not “making judgment.” It is smuggling policy.

To operationalize this, we can represent a judgment-call situation as a triple: uncertainty about state, uncertainty about consequences, and uncertainty about permissible tradeoffs. The first two are epistemic. The third is normative. Good system design is largely the art of not confusing them.

2.2 Reversible vs irreversible decisions

Reversibility is the hinge that turns a difficult decision into a catastrophic one.

A reversible decision is one where, if the system is wrong, the harm can be undone or contained: a temporary block that can be lifted, a safe-mode that can be exited, a medical stabilization step that can be adjusted, a partial rollback that can be reversed. Reversible actions are not harmless, but they preserve the possibility of correction. They are compatible with learning and oversight.

An irreversible decision is one where a wrong choice cannot be repaired at any reasonable cost: loss of life, permanent injury, irreversible legal harm, escalation across strategic thresholds, destruction of critical infrastructure, cascading failure in tightly coupled systems, or reputational/legitimacy damage that cannot be restored by technical fixes. Irreversible actions are not defined only by physical destruction. They include actions that irreversibly alter a person’s standing, freedom, or safety, and actions that irreversibly change the strategic landscape.

The reversibility dimension does something powerful: it tells us where safety must live. In reversible domains, we can tolerate more autonomy because correction is possible. In irreversible domains, autonomy must shrink and governance must expand. Irreversibility is the strongest argument for safe defaults, gating, redundancy, and escalation protocols.

A key implication follows: in high-stakes settings, the system should be designed to prefer reversible first moves. This is not indecision; it is stewardship. It means the system should buy time, stabilize, reduce volatility, gather one more discriminating observation, and avoid commitments that cannot be reversed. The strategic virtue is not "always act," but "do not commit irreversibly on insufficient evidence."

Reversibility also clarifies the relationship between confidence thresholds and permission. The threshold for an irreversible action must be higher than the threshold for a reversible one, even if both actions are technically feasible. This is not simply conservatism. It is proportionality: the certainty requirement should scale with the blast radius of being wrong.

2.3 Low-stakes optimization vs high-stakes governance

Many decisions that look like judgment calls are actually optimization problems in disguise, and many decisions that look like optimization are actually governance decisions in disguise. Confusing the two is one of the central dangers of deploying AGI.

Low-stakes optimization decisions are those where:

- the objective is uncontroversial and has been authorized
- errors are small, local, and correctable
- the decision can be evaluated by stable metrics
- stakeholders accept tradeoffs as routine

Examples include routing deliveries, allocating compute resources, tuning inventory, recommending non-sensitive content, or adjusting a system parameter within a known safe envelope. In these domains, the primary risk is inefficiency. The system can be given wide discretion because the moral stakes are limited and the failure modes are bounded.

High-stakes governance decisions are those where:

- the objective is contested or ethically loaded
- errors harm people, rights, or legitimacy
- the decision redistributes risk across groups
- the decision sets precedent and shapes behavior
- the evaluation metric is incomplete or politically charged

Examples include use-of-force, medical triage, mass surveillance, criminal justice decisions, military escalation thresholds, broad censorship or deplatforming, and actions that can trigger

cascading infrastructure failures. Here, the system is not merely optimizing; it is exercising power. Power without explicit authorization is illegitimate, even if it is statistically "effective."

This distinction matters because optimization problems tempt designers to collapse everything into a single objective function. But governance problems resist that collapse. Governance requires explicit constraints, procedural legitimacy, appeal mechanisms, and accountable authority. It often requires that certain things not be optimized at all, because they are protected by rights or red lines.

For AGI, the practical rule is this: if the decision changes people's rights, safety, or standing in ways that cannot be easily corrected, then it is governance. In governance, the system's role should be bounded: advise, quantify uncertainty, propose options, and implement only within tightly specified constraints. The final authority should remain with accountable human institutions, or with governance mechanisms that are themselves publicly authorized and reviewable.

2.4 When "abstain" is a valid action and when it is not

A common failure pattern in automated systems is forced binary output: the system must say yes or no even when it should say "not sure." For AGI judgment calls, the ability to abstain is often the core safety feature. But abstention is not always possible. The decision class must therefore specify when abstention is valid and what it means operationally.

Abstention is valid when:

- delay does not create disproportionate harm
- the system can move into a safe-mode that reduces risk
- a human or other authority can be reached in time
- additional observation can plausibly resolve the ambiguity
- the system can take a reversible stabilizing action instead of committing

In these cases, abstention is not passive. It is an action: pause, isolate, rate-limit, gather data, escalate, switch to conservative control. The system is still doing something. It is choosing a posture that protects against being wrong.

Abstention is not valid when:

- physics forces immediate action (collision imminent, rapid cascade underway)
- the threat is time-critical and delay is itself catastrophic
- the safe-mode is unavailable or unsafe in context

- communication channels are down and escalation is impossible

In these cases, the system must act, but it should still behave as if abstention were the ideal. It should approximate abstention by choosing the most reversible, least collateral, most conservative action available. This is why reversible-first design is so central: it gives the system something like abstention even when it cannot literally abstain.

This also introduces an important design requirement: systems should be engineered so that abstention is usually available. If a system routinely encounters situations where it must act irreversibly under high uncertainty with no safe-mode, that is not an argument for "better AI." It is evidence of a dangerous system architecture. Good engineering expands the space of reversible, stabilizing moves and reduces the space of cliff-edge commitments.

Finally, abstention forces a governance question: who bears the cost of delay? Sometimes abstention protects the system operator but harms the vulnerable. Sometimes abstention protects the vulnerable but burdens operations. That tradeoff must be decided by legitimate authority in advance. The system should not decide it silently. In other words, even abstention is value-laden. A safe system makes that explicit: abstain according to authorized priorities, not according to implicit institutional convenience.

This completes the shift from intuition to structure. A judgment call becomes a decision class defined by evidential uncertainty, outcome uncertainty, normative tradeoff, reversibility, stakes, and abstention feasibility. Once those dimensions are explicit, subsequent sections can specify the architecture: thresholds, safe defaults, gating, redundancy, and governance mechanisms that keep AGI from turning uncertainty into irreversible harm.

3. Two-Layer Architecture: Facts Versus Authority

If the AGI era teaches one lesson early, it will be this: many disasters attributed to "bad prediction" are actually disasters of "bad authority." The system did not merely misread the world; it acted as if it had permission to choose whose interests to prioritize, which risks to impose, and which harms to accept. Humans constantly blend facts and values in the same sentence, so the blend feels natural. Machines make the blend dangerous because they can scale it, conceal it inside pipelines, and present it with the glow of objectivity.

A practical response is a two-layer architecture: an epistemic layer that handles beliefs about the world, and a normative layer that defines what the system is allowed to do. The epistemic layer answers, "What is happening and how confident are we?" The normative layer answers, "Given our authorized values and constraints, what actions are permitted or required?" In a mature system, these layers are not philosophical decorations. They are separate modules with

separate inputs, separate failure modes, and separate accountability. Their separation prevents one of the most common pathologies in automated decision-making: treating a preference as if it were a fact, and treating an output as if it were destiny.

This section develops that architecture, shows how probability and permission must be disentangled, and explains the danger of moral laundering: the conversion of contested value decisions into seemingly factual conclusions.

3.1 Epistemic layer: what is known, what is inferred, what is unknown

The epistemic layer is the system's disciplined relationship to reality. Its purpose is not to sound smart. Its purpose is to represent uncertainty honestly and usefully.

At minimum, the epistemic layer should produce four kinds of outputs.

First, it must separate observations from inferences. Observations are sensor readings, logs, reports, measurements—things that can be traced to sources with known error characteristics. Inferences are hypotheses about underlying state: "this vehicle is about to collide," "this account is fraudulent," "this patient is in septic shock," "this crowd is turning violent." A system that presents inferences as observations is already unsafe because it hides the inferential step where uncertainty lives.

Second, it must quantify confidence in ways that are calibrated, not theatrical. The point of a confidence score is not to justify action; it is to signal whether action should be deferred or gated. Calibration means that when the system says "90%," it is right about nine times out of ten under conditions similar to those now present. This is difficult in the real world, especially under distribution shift. But the direction is clear: confidence must be tested, stress-tested, and corrected, not merely emitted.

Third, it must name what it does not know. "Unknown" is not a defect; it is a safety signal. Unknowns appear as missing variables, ambiguous evidence, sensor failure, contradictory reports, novelty relative to training, or adversarial conditions. An epistemically mature system does not collapse unknowns into the nearest known pattern. It surfaces them as uncertainty that affects decisions.

Fourth, it must detect when its own knowledge is unreliable. This is the distribution shift problem: the world is now unlike the system's historical experience. A system that cannot detect shift is like a pilot with a frozen altimeter: it continues to act confidently while the ground approaches. The epistemic layer should therefore include explicit "out-of-distribution" or "low reliability" flags that trigger conservative action and escalation.

In human terms, the epistemic layer corresponds to the virtues of attention, humility, and honesty. In engineering terms, it corresponds to uncertainty modeling, calibration, shift

detection, provenance tracking, and clear internal separation between data and hypothesis. Without this layer, any normative policy is applied blindly. But without the normative layer, epistemic competence becomes dangerous power.

3.2 Normative layer: who sets values, constraints, and red lines

The normative layer is the system's constitution. It is where legitimacy lives.

This layer specifies what the system is optimizing, what it must never do, what it must always do, and what it must escalate. It also specifies who is authorized to set these rules and how they are updated. That "who" is not an abstract question. It is the heart of governance. In human society, values are set by a mix of law, professional standards, organizational policy, community norms, and moral commitments. In a technical system, these sources must be translated into explicit constraints and procedures.

The normative layer includes at least five elements.

First, objectives: the goals the system is allowed to pursue, including what counts as success and how to balance competing objectives. For low-stakes systems, a single objective may be acceptable. For high-stakes systems, objectives must be plural and constrained.

Second, constraints: hard bounds that cannot be traded away, even for efficiency. Constraints often encode rights, safety requirements, and procedural rules. They are not "penalties" in an optimization function; they are limits on what the system may do.

Third, red lines: actions that are categorically forbidden or require higher authority. Red lines are especially important in irreversible domains. They prevent a system from drifting into catastrophic territory because "it seemed optimal."

Fourth, escalation policies: rules for when the system must hand off to accountable authority. Escalation is not a failure of intelligence; it is a recognition of legitimacy. When a decision hinges on contested values, the system should not decide; it should present options and consequences to the authorized decision-maker.

Fifth, accountability hooks: documentation requirements, reason packets, logging rules, review cadence, and appeal mechanisms. Even when the system acts quickly, it must act in a way that can be meaningfully reviewed when review is possible.

The normative layer should also specify default postures for uncertainty: whether the system should bias toward caution or action, and how that bias changes with reversibility and stakes. These defaults are moral decisions, not technical ones, because they determine who bears the cost of error: the person mistakenly harmed by action, or the person harmed by inaction.

In short, the normative layer is where society's values become operational. Without it, the system will create its own values implicitly, through proxy metrics and training artifacts. That is precisely what must be avoided.

3.3 Separating probability from permission

The central technical-social confusion in judgment calls is the substitution of "likely" for "allowed." A system may believe an outcome is likely, but still lack permission to act on that belief.

Probability answers questions like:

- How likely is this hypothesis given the evidence?
- How likely is harm if we take action?
- How likely is harm if we do not take action?

Permission answers questions like:

- Are we allowed to impose this risk on this person?
- Are we allowed to act without consent?
- Are we allowed to escalate this process?
- Are we allowed to trade this harm for that benefit?

A mature AGI system must treat these as separate gates. The epistemic layer may output a high probability. The normative layer may still block the action if it violates constraints, crosses a red line, or requires human authorization. Conversely, the normative layer may require action even at moderate probability if the authorized policy is to prioritize preventing a particular kind of harm, provided the action is reversible and constrained.

This separation also clarifies the meaning of confidence thresholds. Thresholds are not purely statistical. They embody a normative choice about acceptable error. The threshold for acting is set by policy, not by the model's internal sense of plausibility. The model provides calibrated probabilities; the normative layer maps those probabilities to permitted actions using explicit rules. This prevents the system from silently shifting the threshold as conditions change or as the model becomes overconfident.

In practical terms, separating probability from permission means designing decision pipelines like this:

- Estimate state and uncertainty.

- Identify candidate actions and their predicted consequences.
- Check each candidate action against constraints and red lines.
- If multiple actions are permitted, select among them using authorized priorities.
- If no action is permitted, enter safe-mode and escalate.

This may sound bureaucratic, but it is exactly what prevents "smart" systems from becoming unaccountable actors. A system can be very accurate and still be illegitimate. Permission is how legitimacy is encoded into the machine's behavior.

3.4 Avoiding moral laundering: when value choices masquerade as facts

Moral laundering occurs when a value decision is hidden inside a factual claim. It is the conversion of "we chose this tradeoff" into "the data says so." This is one of the most corrosive failure modes of automated systems because it removes human agency from moral decisions while preserving human blame when things go wrong.

Moral laundering appears in several common forms.

One form is metric substitution. The organization says it wants "fairness," but measures it as "equal error rates," or says it wants "safety," but measures it as "absence of reported incidents," or says it wants "truth," but measures it as "engagement with reputable sources." The metric is not the value. It is a proxy. When the system optimizes the proxy, it often violates the value, and then the organization claims the outcome is "data-driven."

A second form is threshold invisibility. The system outputs a binary decision—approve/deny, intervene/ignore—without showing the confidence threshold and without acknowledging that the threshold reflects a moral choice about which errors are tolerable. When the threshold is hidden, it becomes unchallengeable. People cannot contest the value choice because it is disguised as an engineering parameter.

A third form is collapsing contestable categories into "ground truth." For instance, labeling someone as "high risk" or a situation as "threatening" often encodes cultural assumptions and institutional incentives. If the system is trained on historical labels, it inherits the past's judgments and then presents them as objective reality. This is not merely bias in the abstract; it is the laundering of historical power into present authority.

A fourth form is narrative certainty. The system produces explanations that sound like reasons but are actually post-hoc rationalizations. The explanation gives the impression that the decision was compelled by facts, when it was actually shaped by hidden priors and goals. This undermines legitimacy because it makes the system seem accountable while keeping its real decision drivers opaque.

Avoiding moral laundering requires procedural discipline.

First, the system must expose where value choices occur: objectives, constraints, thresholds, and defaults. Second, it must distinguish descriptive statements ("we estimate a 30% chance of X") from normative statements ("we are authorized to act if chance exceeds 20%"). Third, it must maintain explicit documentation for these normative settings: who set them, when, under what authority, and how they are reviewed. Fourth, it must preserve the option for contestation and appeal, at least in domains where people's rights and standing are affected.

The point is not to eliminate values. Values are inevitable. The point is to keep values visible, authorized, and accountable. When values are hidden, the system becomes a covert legislator. When values are explicit, the system can be a disciplined instrument of legitimate policy.

This two-layer architecture provides the foundation for the rest of the paper. Once facts and authority are separated, we can design safe defaults and thresholds without pretending they are neutral. We can build escalation protocols that treat legitimacy as a first-class constraint. And we can treat "judgment calls" not as mystical human intuition, but as a governable decision class with explicit boundaries: what the system may infer, what it may recommend, and what it is permitted to execute.

4. Binary Decisions Done Right: Thresholds, Defaults, and Error Asymmetry

Binary decisions feel like clarity because they compress an entire causal universe into one bit. Yet in the real world, yes/no decisions are rarely "purely factual." They are decisions made under uncertainty, where the costs of being wrong are distributed unevenly across people and time. This is why binary calls are one of the most dangerous places to deploy AGI without discipline: the system's apparent decisiveness can be mistaken for moral legitimacy, and its speed can outrun the human ability to notice drift.

The central claim of this section is that binary decisions can be made safer, not by demanding perfect prediction, but by engineering the decision pipeline around three commitments. First, decide explicitly which error is less acceptable for each domain. Second, implement that decision through confidence gating and pre-authorized thresholds, including a safe-mode region when uncertainty is too high. Third, prevent "confidence theater" by calibrating probabilities against base rates and shift conditions. In this frame, the binary output is not the heart of the system. The heart is the structure that determines when a binary output is allowed to trigger action.

4.1 False positives vs false negatives and why the acceptable error differs by domain

Any binary decision defines two kinds of mistakes.

A false positive occurs when the system says “yes” in a situation where the correct answer is “no.” It acts when it should not act. A false negative occurs when the system says “no” where it should have said “yes.” It fails to act when action was warranted. These are not symmetric errors. They hurt different people, create different kinds of harm, and carry different moral weight in different domains.

Humans intuit this, often subconsciously. But systems must encode it explicitly, because a “balanced” model optimized for overall accuracy can be ethically perverse. The ethically acceptable error profile depends on what “yes” and “no” do in the world.

In use-of-force contexts, false positives are morally intolerable because action can kill or permanently harm an innocent person. The bias must therefore be toward restraint: require very high confidence and strong procedural justification to act. A system that is “more accurate than humans on average” is not acceptable if its residual errors include even rare catastrophic false positives.

In medical triage, the error asymmetry may be reversed for certain interventions. A false negative can mean failing to stabilize a patient who could have been saved, while a false positive may mean administering a reversible intervention that carries limited harm. Many emergency protocols already embed this logic: stabilize first, refine later. Here “act” often means “perform reversible stabilization,” not “execute irreversible procedure.” The acceptable error profile hinges on reversibility.

In fraud detection, a false positive can unjustly punish innocent people by denying access to money or services, while a false negative permits theft and may harm many victims. The acceptable balance depends on the stakes, the availability of appeal, and the reversibility of the intervention. It is ethically different to temporarily flag and request verification than to permanently freeze assets without explanation.

In critical infrastructure, both error types can be catastrophic depending on the intervention. A false positive shutdown can trigger cascading failures, but a false negative failure to isolate an intrusion can spread damage. The correct posture often becomes layered: first take a low-collateral containment step, then escalate only if evidence strengthens.

The lesson is general. Error asymmetry is a normative choice that cannot be left to the model. Even if a model optimizes a loss function that weights errors differently, those weights embody policy. They must be set by legitimate authority, reviewed, and justified. Otherwise the system is “making moral decisions” under the cover of statistical optimization.

A practical method is to begin every binary decision design with a question: if we must be wrong, which wrong is less acceptable, and why? The answer defines the domain's default posture, thresholds, escalation rules, and what safe-mode means.

4.2 Confidence gating: pre-authorized thresholds for yes, no, and safe-mode

Once error asymmetry is explicit, the next step is to translate it into operational gates. The simplest structure is not a single threshold, but three regions.

A "yes" region: confidence is high enough that acting is authorized. A "no" region: confidence is low enough that acting is not authorized. And between them, a "safe-mode" region: uncertainty is too high for decisive action, so the system must choose a conservative reversible posture or escalate to human authority.

This three-region design is essential because it creates room for epistemic humility. It prevents the system from being forced into a binary decision when the world has not supplied enough evidence. It also prevents the organization from quietly turning uncertainty into action by default.

Confidence gating must be pre-authorized. That means the thresholds are set in advance by policy, not chosen dynamically by the model in the moment. The model's role is to provide calibrated estimates of relevant probabilities. The normative layer's role is to map those estimates to permitted actions.

In practice, confidence gating can be implemented as a decision pipeline:

- The epistemic layer produces a probability distribution over hypotheses and confidence intervals, plus shift signals.
- The system evaluates candidate actions, including "do nothing," "safe-mode action," and "irreversible act."
- Each action has a required confidence threshold proportional to its irreversibility and blast radius.
- If no action meets its threshold, the system must select the safest reversible action available and escalate.

This makes two things explicit. First, "confidence" is not one number. It may include uncertainty about sensors, uncertainty about classification, and uncertainty about downstream consequences. Second, thresholds are not merely technical. They encode who we are willing to harm by being wrong.

The safe-mode region deserves special emphasis. In high-stakes systems, safe-mode is not a passive "wait." It is an active risk-minimizing posture: slow down, isolate, rate-limit, stabilize, gather additional data, or hand off control. The system's obligation in safe-mode is to reduce the chance of irreversible harm while preserving the possibility of later correction.

4.3 Domain-sensitive default actions: deny-by-default, act-by-default, or safe-mode

Thresholds alone do not guarantee safety. Any binary pipeline has a default action when confidence is ambiguous or when the system fails to produce a reliable estimate. The default is where moral reality hides.

There are three broad default postures, each appropriate in different domains.

Deny-by-default: When "yes" imposes irreversible harm, restraint must be the default. If the system cannot establish high confidence, it should say no, or choose a non-harmful alternative. This is appropriate for actions that directly threaten life, liberty, or irreversible status. Deny-by-default is not "do nothing." It may still require action, but the action is constrained to be non-catastrophic and reversible.

Act-by-default: When inaction is itself highly likely to cause severe harm and the available action is reversible or low-collateral, action may be the default. This posture is common in emergency stabilization settings, but it must be narrowly defined. "Act" here cannot mean "take the most extreme intervention." It means "take the safest reversible step that reduces immediate risk."

Safe-mode-by-default: When both action and inaction can be harmful and the system's certainty is inadequate, safe-mode should be the default. Safe-mode is a controlled posture designed to buy time and reduce volatility. This is often the best default in cyber-physical systems, autonomous systems, and complex organizational processes.

The most common institutional failure is to leave the default implicit. Systems are deployed with a quiet drift toward action because action produces throughput, reduces staffing demands, and creates an appearance of efficiency. Over time, the safe-mode region is minimized, escalation is discouraged, and the system becomes a de facto autonomous actor. This is how "automation bias" becomes policy: humans stop questioning the system because the system seems to keep things running.

Domain-sensitive defaults must therefore be codified and defended as moral choices. They should be documented, reviewed, and stress-tested. The question is not "what makes the system most productive?" but "what default keeps the system within legitimate and safe bounds when it is wrong?"

A useful rule is proportionality: the more irreversible the “yes,” the more conservative the default must be. The more reversible and information-gaining the action, the more plausible an act-by-default stance becomes.

4.4 Calibration and base rates: preventing systematic overconfidence

Even a beautifully designed threshold system collapses if probabilities are not trustworthy. Overconfidence is the classic failure mode of pattern-recognition systems, and it becomes catastrophic when paired with high authority.

Calibration is the requirement that probability estimates correspond to reality over time. If the system says “80%,” it should be right about eighty times out of a hundred in comparable conditions. Without calibration, confidence thresholds become meaningless rituals. The system may cross the “yes” threshold frequently while being wrong more often than the policy intended.

Base rates are the second half of the problem. Many high-stakes events are rare: actual threats, true fraud, imminent catastrophe, severe adverse reactions. If a system ignores base rates, it will generate floods of false positives or become complacent and miss real events. Humans are famously bad at base-rate reasoning under stress; machines can be too, especially if trained on non-representative data or if deployed in environments where the underlying rate shifts.

Preventing systematic overconfidence requires several disciplines.

First, continuous calibration testing under realistic conditions, not just on curated benchmarks. Models must be evaluated on data that reflect deployment distributions, including edge cases and adversarial behavior.

Second, explicit handling of distribution shift. When the world changes, prior calibration breaks. The system must detect shift and respond by increasing uncertainty, widening safe-mode, and escalating more often. This is not a weakness. It is the system recognizing that its authority should shrink when its knowledge is less reliable.

Third, base-rate awareness in decision thresholds and outputs. The system must incorporate prior probabilities and must communicate when a positive signal is still unlikely to be true because the event is rare. This is particularly important in domains like security screening, fraud detection, and early warning, where even high sensitivity can produce mostly false alarms if the event rate is low.

Fourth, separation of ranking from acting. Many systems can rank cases for human review rather than autonomously acting. Ranking can be highly useful even with imperfect calibration, because humans remain the final authority. Autonomous action, by contrast, requires stronger calibration and tighter constraints.

Fifth, discipline against feedback loops. When a system acts, it changes the data it later sees. If it flags certain populations more, it will "discover" more incidents there, not necessarily because incidence is higher, but because scrutiny is higher. This can reinforce bias, inflate confidence, and distort base rates. A well-designed system must correct for these selection effects and must avoid treating its own outputs as ground truth.

The overall point is simple. Binary decisions are not saved by intelligence alone. They are saved by humility engineered into thresholds, defaults, and calibration. The acceptable error profile must be chosen, not discovered. The boundaries of permission must be explicit, not implied. And probability must be honest, not performative. When these disciplines are in place, "yes/no now" becomes less like a cliff-edge leap and more like a controlled decision process with safe regions, reversible moves, and governance that survives uncertainty.

5. The Third Option: Designing for Abstention and Safe-Mode

Binary decision systems fail most often not because they choose the wrong branch, but because they are forced to choose a branch at all. The world frequently presents situations where neither "yes" nor "no" is justified at the moment of action, yet action is still required. Humans handle this with a kind of improvised third option: stall, hedge, ask for help, take a small reversible step, or buy time. That third option is one of the most important safety properties of human judgment, even when humans execute it imperfectly.

AGI systems must be designed to have an equivalent third option, but formalized: abstention and safe-mode. This is not a luxury feature. It is the core mechanism that prevents uncertain inference from becoming irreversible harm. Safe-mode is the system's way of saying: the environment is ambiguous, the risk is high, so I will move into a posture that reduces blast radius, preserves reversibility, and escalates to legitimate authority when available.

The deeper point is that "I'm not sure" must be treated as a valid, stable output state. In many organizational cultures, uncertainty is treated as weakness, and automation is used to create the appearance of decisiveness. Safe-mode design is a refusal of that illusion. It treats epistemic humility as an engineered capability.

5.1 Why "I'm not sure" must be operationally allowed

If an AGI is required to output yes/no at every moment, it will eventually produce confident nonsense under pressure. The system may be statistically well-trained and still be forced into decisions that its evidence cannot support. In those moments, the system will either guess, or it will hallucinate certainty. Both behaviors are dangerous because they translate epistemic limits into real-world actions.

Operationally allowing “I’m not sure” does three things.

First, it prevents error amplification. When uncertainty is high, the cost of making a wrong decisive move often exceeds the cost of delay or conservative posture. If the system can declare uncertainty and shift into safe-mode, it avoids making the highest-commitment move at the worst moment.

Second, it protects legitimacy. Many judgment calls involve contested values. If the system cannot cleanly map the evidence to a single permitted action, it should not silently pick a side. “I’m not sure” is a signal that the decision is in the normative gray zone and must be escalated to human authority or resolved by pre-authorized policy.

Third, it stabilizes human-system interaction. Humans trust systems that know what they don’t know more than systems that always sound certain. In high-stakes contexts, overconfidence is a moral hazard: it invites operators to defer when they should intervene. A system that can abstain, and does so reliably under uncertainty, creates a healthier relationship: humans see it as an instrument, not an oracle.

Allowing abstention is also a design commitment. It means building workflows, staffing, and interfaces that can accept abstention without punishing it. If operators are penalized for delays, or if organizational incentives reward throughput above safety, the system will be tuned to minimize abstention. Over time, safe-mode shrinks, and the system becomes a covert autonomous authority. In other words, abstention must be protected both technically and institutionally.

5.2 Safe-mode patterns: slow, isolate, degrade, rate-limit, handoff

Safe-mode is not one behavior; it is a family of patterns. The common structure is that safe-mode reduces the system’s capacity to do harm while preserving enough function to remain useful.

Slow: The system reduces speed, cadence, or aggressiveness to gain time and reduce kinetic or cascading risk. In physical domains, slowing down can be the difference between a reversible correction and an irreversible crash. In organizational domains, slowing decisions can prevent compounding errors and allow human oversight to catch up.

Isolate: The system segments the environment to contain potential damage. In cybersecurity, isolation might mean quarantining a network segment. In infrastructure, it might mean separating subsystems. In information systems, it might mean limiting propagation of an unverified update. Isolation is often the safest first response when the system suspects abnormality but cannot identify its nature.

Degrade: The system reduces functionality to a known-safe subset. Degradation is not failure; it is controlled retreat. For an autonomous vehicle, it might mean limiting to a minimal control policy. For a decision system, it might mean switching from autonomous action to recommendation-only. Degradation preserves service at reduced risk.

Rate-limit: The system constrains the number or magnitude of actions per unit time. Rate limits are critical in preventing runaway cascades caused by feedback loops, adversarial exploitation, or systemic miscalibration. If the system is wrong, rate limiting ensures it is not wrong at scale instantly.

Handoff: The system transfers control to another agent: a human, a supervisory system, or a specialized fallback controller. Handoff requires that someone is available, that interfaces are usable under stress, and that the handoff itself does not create confusion. In practice, handoff is often the hardest safe-mode pattern because it depends on organizational readiness, not only technical design.

These patterns can be combined. A system can slow and isolate while preparing a handoff. It can degrade and rate-limit while requesting human confirmation. The point is that safe-mode should be a designed posture with explicit triggers and predictable behavior, not an improvisation at the moment of crisis.

5.3 Information-gaining moves: buying time without pretending certainty

Safe-mode is most powerful when it is not merely conservative, but information-gaining. The system should take actions that reduce uncertainty while reducing risk, so that it can either return to normal operation or escalate with a clearer picture.

Information-gaining moves have three properties.

First, they are reversible or low collateral. The system should not “probe” by taking actions that harm people or cross red lines. The probe must be safe.

Second, they are diagnostic. The system chooses an action that will distinguish among competing hypotheses. For instance, if a cyber intrusion is suspected, the system might isolate and monitor specific traffic patterns. If a sensor is ambiguous, the system might reposition to obtain a clearer measurement. If a financial anomaly is detected, the system might require verification rather than executing a permanent denial.

Third, they are time-buying. They create a buffer in which more evidence can arrive or human oversight can engage. The essence of many crises is time compression. An information-gaining move expands time by reducing immediate risk.

This is the engineered version of a human virtue: when unsure, do the smallest safe thing that increases clarity. Humans do this when they step back from a ledge, ask one more question, call for a second opinion, or stabilize a patient before diagnosis is complete. In AGI systems, this virtue must be designed into the action space. If the system has no low-collateral options, it will be forced into high-collateral ones.

Information-gaining moves also help prevent a subtle pathology: the need to "sound decisive." If the system can take constructive action that is explicitly framed as uncertainty reduction, it avoids the pressure to output a confident yes/no. It can say, in effect: I do not yet know enough to commit, so I am taking a safe step to learn.

5.4 When safe-mode becomes unsafe: time-critical boundary conditions

Safe-mode is not universally safe. There are boundary conditions where slowing, isolating, or waiting can increase harm. A safe-mode posture that is correct in one domain can be catastrophic in another.

In time-critical physical systems, delaying action can turn avoidable harm into inevitable harm. If collision is imminent, "abstain" is not a meaningful option. If a system detects a rapidly spreading failure, isolation delays can allow the cascade to outrun containment. In emergency medicine, delay can cause irreversible physiological damage. In security contexts, hesitating can allow an attack to complete.

This does not mean safe-mode should be abandoned. It means safe-mode must be defined with time-critical constraints. A mature architecture will include:

- time-to-impact estimation
- a minimal fallback controller for immediate hazards
- thresholds that shift as time horizons shrink
- pre-authorized emergency actions limited to reversible or bounded interventions
- escalation protocols that are rapid and unambiguous

In other words, even when abstention is impossible, the system should approximate safe-mode by choosing the least collateral action available. The design objective is to avoid cliff-edge commitments under uncertainty, but the system must still act when physics forces action. The correct response is layered control: a fast, conservative safety controller handles immediate hazards, while the higher-level AGI refrains from irreversible discretionary actions unless authorized and sufficiently confident.

A second boundary condition is social and organizational. Safe-mode can become unsafe when it is routinely abused or misunderstood. If a system enters safe-mode too often, operators may ignore it, override it reflexively, or disable it. If safe-mode triggers are opaque, humans may misinterpret them as system failure rather than protective behavior. If safe-mode creates operational costs that are not budgeted, leadership may quietly pressure engineers to reduce abstentions. Over time, the system's safety posture erodes.

Therefore, safe-mode design must include human factors: clear signals, predictable behavior, training, and institutional incentives that treat safe-mode as success under uncertainty rather than as embarrassing failure. This is especially important in "no-audit" domains. If the organization resents safe-mode because it slows operations, it will optimize it away until catastrophe occurs.

The section's conclusion is straightforward. The third option is not indecision; it is engineered humility. Abstention and safe-mode are the mechanisms that allow an AGI to remain a tool rather than an autonomous moral actor. They preserve reversibility, maintain legitimacy, and reduce the chance that uncertainty becomes irreversible harm. In the next sections, we build on this by showing how reversibility-first design, layered action tiers, and gating architectures can formalize safe-mode into a practical safety envelope across domains.

6. Reversibility First: Minimizing Irreversible Commitments

The simplest way to describe the safety problem in high-stakes judgment calls is this: mistakes become disasters when the system commits irreversibly before it has earned the right to be certain. The world is noisy, time is short, and even excellent models are sometimes wrong. The design response is not to demand perfection. It is to structure action so that early moves preserve the possibility of correction.

"Reversibility first" is therefore not a philosophical preference; it is a practical engineering ethic. It says: when uncertainty is present, choose actions whose harms can be undone, contained, or compensated, and delay irreversible commitments until confidence is high, authority is clear, and the action is truly necessary. This principle appears in mature human domains already. In emergency medicine, stabilize before definitive diagnosis. In aviation, aviate first, then navigate, then communicate. In safety engineering, fail-safe before fail-operational. In governance, due process before punishment.

For AGI, reversibility-first becomes the backbone of safe judgment. It shapes thresholds, default actions, safe-mode design, and escalation protocols. It also shapes what we allow the system to do autonomously. If a system is authorized to act quickly, it should be authorized primarily for

reversible containment and stabilization, not for irreversible punishment, violence, or strategic escalation.

6.1 Reversible-first as a design principle

Reversible-first is best understood as a constraint on the action space. Instead of asking, “What is the best action?” the system asks, “What is the best reversible action that reduces risk and preserves future choice?”

This principle has three components.

First, preference for reversibility under uncertainty. When the system’s epistemic layer signals ambiguity, the normative layer should bias toward actions that can be undone. This bias should not be left to ad hoc heuristics; it must be codified. The more uncertain the world, the less authority the system should exercise over irreversible outcomes.

Second, proportionality between irreversibility and evidence. If an action cannot be undone, the evidence threshold must be correspondingly higher. In other words, irreversibility should be expensive in epistemic currency. This is not simply caution. It is the recognition that irreversible harm is morally different from reversible inconvenience.

Third, separation between stabilization and resolution. Many crises tempt a system to leap straight to resolution: identify the culprit, punish, shut down, strike, ban, arrest, purge. Reversible-first insists that the first job is stabilization: prevent immediate harm, prevent cascade, preserve options. Resolution can come later, often with human authority and due process.

One can treat reversible-first as a kind of “moral friction.” It slows the system precisely when the system is most tempted to act decisively on limited information. This friction is not inefficiency; it is stewardship.

6.2 Tiers of action: from alert to temporary intervention to irreversible acts

Reversible-first becomes concrete through tiered action. The core idea is that “action” is not one thing. It comes in levels of commitment. A safe system does not jump from observation to maximum force. It escalates through tiers, and each tier has different confidence requirements and different authorization requirements.

A typical tier structure might look like this.

Tier 0: Log and monitor. The system records the anomaly, increases attention, and prepares diagnostics, but does not intervene. This is appropriate when the risk is low or evidence is weak.

Tier 1: Alert and recommend. The system notifies a human operator or supervisory system, provides a reason packet, and recommends next steps. This is a low-collateral move that preserves human authority.

Tier 2: Soft friction. The system adds reversible friction: request verification, require a second factor, slow a process, add a manual check, or increase scrutiny. This tier is especially important in domains like fraud and access control because it reduces harm without imposing irreversible penalties.

Tier 3: Temporary containment. The system takes reversible containment actions: isolate a subsystem, quarantine an account, limit privileges, slow a machine, route away from a hazard, or switch to a conservative controller. These actions are meant to prevent cascade and buy time.

Tier 4: Strong intervention with fast appeal. The system blocks, disables, or restrains in a way that has serious consequences but remains reversible with timely review. This tier demands higher confidence and stronger governance because it risks unjust harm.

Tier 5: Irreversible action. This includes lethal force, permanent deprivation of rights, irreversible medical procedures, strategic escalation actions, or physical destruction. In well-designed systems, this tier is rare, heavily gated, and often prohibited for autonomous execution.

The specific tiers vary by domain, but the logic is stable: early tiers are reversible and information-gaining; later tiers are more decisive and require stronger evidence, stronger authorization, and often human confirmation. Tiering prevents the cliff-edge where a single classification error triggers irreversible harm.

6.3 Designing systems so that the first move is rarely the last move

A dangerous system is one where the first move commits the system to a path with no return. The safe alternative is to design a system where the first move is usually a step that can be revised as new information arrives. In other words, the system should behave like a good human practitioner: take the minimum safe action now, then update.

This requires architectural commitments.

First, action must be decomposable. Instead of a single “execute” function, the system must have a sequence: detect, stabilize, verify, escalate, confirm, resolve. Each step has its own thresholds and permissions.

Second, the system must be able to revise earlier assumptions without shame. Many machine learning systems are not naturally designed for graceful backtracking. They commit to a label

and then optimize around it. A reversibility-first architecture treats early labels as provisional. It makes provisionality explicit: “suspected intrusion,” “possible fraud,” “uncertain hazard.” It then designs actions that are appropriate for provisional states.

Third, the system must preserve optionality by maintaining pathways back to normal operation. Safe-mode must be an exit-capable state, not a dead-end. Containment must have release criteria. Temporary holds must have review deadlines. Without exit pathways, reversibility is fictional.

Fourth, the system must prevent escalation lock-in. In many crises, once an intervention begins, institutional momentum pushes toward further escalation, even if evidence weakens. Automated systems can accelerate this momentum through feedback loops: intervention generates new data that appears to justify the intervention. Designing the first move to be rarely the last move requires deliberate countermeasures: independent review, cooling-off periods for irreversible steps, and checks that treat new “evidence” produced by the system’s own actions with skepticism.

The result is a system that does not pretend it can “solve” a crisis instantly. It can stabilize, learn, and hand off. Its role is to keep the situation within the bounds of reversibility until legitimate authority can decide what resolution is justified.

6.4 Reducing collateral: bounded interventions and safety envelopes

Reversibility-first is not only about whether an action can be undone. It is also about how much collateral harm an action imposes while it is in effect. Many “reversible” actions can still be devastating if their scope is too broad or their duration too long. A temporary shutdown of a critical system can kill people. A temporary freeze of funds can destroy a business. A temporary denial of mobility can endanger someone. Reversibility is necessary, but not sufficient.

This is where bounded interventions and safety envelopes matter.

A bounded intervention is an action constrained in scope, magnitude, and duration. It is targeted rather than broad, limited rather than open-ended, and designed to minimize harm if it turns out to be mistaken. Boundedness can be implemented through:

- narrow targeting (only the suspected component, not the whole system)
- least-privilege reduction (restrict to minimal safe operations)
- time limits (automatic expiration unless renewed by authorized review)
- geographic or functional limits (contain within a safe region)
- gradual ramps (increase intervention strength only if evidence strengthens)

Safety envelopes are more general: they define a region of allowed behavior within which the system can operate autonomously. Outside the envelope, the system must escalate, slow, or hand off. In autonomous vehicles, safety envelopes might constrain speed, following distance, and maneuver aggressiveness. In cybersecurity, they might constrain automated changes to permissions or network routing. In organizational decision systems, they might constrain which actions can be taken without human approval, especially those affecting rights and status.

Safety envelopes also help manage distribution shift. When the environment becomes unfamiliar, the system can shrink its envelope: reduce autonomy, restrict actions, and rely more on human oversight. This is a disciplined way to respond to uncertainty: authority contracts as knowledge becomes less reliable.

Collateral reduction is also a legitimacy issue. People accept interventions more readily when they are targeted, time-limited, and transparent about uncertainty. Overbroad interventions breed distrust and resistance, which can itself worsen safety by causing operators to ignore system warnings or disable safe-mode behaviors. A system that minimizes collateral is not only safer technically; it is safer socially.

This section's conclusion is that reversibility-first is the practical heart of safe AGI judgment. It turns uncertainty into conservative action, transforms binary calls into tiered escalation, and prevents the system from committing irrevocably before it has earned the epistemic and moral right to do so. In the next section, the paper will extend this logic to the extreme case: no-audit scenarios, where the whole purpose of design is to ensure that no single inference can trigger an irreversible catastrophe.

7. No-Audit Scenarios: When Post-Mortems Cannot Be the Safety Plan

Much of modern safety culture assumes that failure is survivable. We learn by investigating accidents, tracing causal chains, and revising procedures. This is how aviation, medicine, and industrial engineering have improved over decades: tragedy produces knowledge, and knowledge reduces the chance of repetition. That logic depends on a quiet premise—that there will be something left to investigate and someone left to improve the system.

No-audit scenarios violate that premise. They are decision contexts in which a single wrong action can erase evidence, destroy the system, kill the witnesses, or trigger cascades so large that reconstruction becomes impossible. In these scenarios, post-mortems are not merely insufficient; they may be fantasy. The consequence is a shift in the entire safety posture. If learning after failure is not available, then the primary safety mechanism cannot be "detect and correct." It must be "constrain and prevent."

This section names what “nothing left to audit” implies, shows why single-point agency becomes unacceptable, and argues for a hard design principle: no single inference should be able to end the world. This is not rhetorical. It is a structural requirement for systems that operate near catastrophic thresholds.

7.1 What “nothing left to audit” really implies

The phrase “nothing left to audit” can mean several different things, and each one matters for system design.

Sometimes it is literal physical destruction. The system acts, the environment is destroyed, and there is no record. In extreme cases, the act itself is the erasure: a kinetic strike, a runaway industrial event, a catastrophic autonomous maneuver, a lethal intervention. Even if black-box logging exists, the broader context—the human intentions, the chain of authority, the adversarial pressures—may be unrecoverable.

Sometimes it is cascading systemic failure. The initial decision triggers a chain reaction in tightly coupled systems: power grids, financial systems, logistics networks, communication infrastructure. In such cascades, the original triggering decision may be lost inside the avalanche. After the event, investigators may see only the final collapse, not the subtle initial misstep that made collapse inevitable.

Sometimes it is geopolitical or social irreversibility. A decision triggers escalation across strategic thresholds, and the world cannot return to the prior state even if the original decision is later judged wrong. A false alarm that triggers retaliation, an automated response that violates sovereignty, an action that collapses trust between institutions—these can be irreversible even if no physical system is destroyed.

Sometimes it is epistemic irreversibility. The system acts in a way that permanently contaminates the evidence. In legal contexts, coercive interrogation can corrupt testimony. In cyber contexts, aggressive remediation can destroy forensic traces. In organizational contexts, premature public accusation can poison the information environment. The “audit” becomes impossible because the act itself alters the truth-trace.

Across these cases, the shared implication is that we cannot rely on feedback from catastrophe to tune the system. If catastrophe is the teacher, the tuition is unacceptable. Therefore safety must come from structural constraints that make catastrophic acts difficult to trigger, even under strong pressure.

This is the defining difference between ordinary high-risk systems and existential-risk systems. In ordinary systems, we can tolerate occasional failure if we learn rapidly and reduce recurrence. In no-audit systems, occasional failure is not a learning opportunity; it is an

endpoint. The design goal shifts to catastrophe avoidance under uncertainty, not continuous improvement through tragedy.

7.2 Single-point agency as an unacceptable failure mode

When the potential harm is catastrophic and irrecoverable, the most dangerous architectural feature is single-point agency: a situation where one component, one model, one pipeline, or one decision pathway can produce a final irreversible action.

Single-point agency is unacceptable for two reasons.

First, all components fail. Sensors fail, models drift, operators misunderstand, organizations mis-specify goals, adversaries manipulate signals, and black swans occur. If a single component can end the world, then the system is only as safe as its weakest moment. That is not a tolerable posture when stakes are existential.

Second, single-point agency collapses legitimacy. If catastrophic action can be triggered by one model's inference, then authority has been implicitly delegated to that model, whether or not anyone intended it. After a catastrophe, survivors—if there are any—will discover that no human truly chose the outcome. It "just happened," because the system was designed to allow it. This is the ultimate form of moral abdication: power without agency and harm without accountable choice.

The presence of single-point agency is often not obvious. It can be hidden in automation chains: a recommendation becomes a default, a default becomes an auto-execute, an auto-execute becomes embedded in emergency procedures, and soon no one remembers that the machine is the final trigger. In complex organizations, responsibility diffuses and pipelines become "the way things are done." A design that began as advisory can silently become decisive.

Therefore, no-audit system design must treat any path to catastrophic action as a controlled pathway with multiple independent gates. If any single component can bypass the gates, the gates are not real.

7.3 Catastrophic irreversibility and the need for structural prevention

In ordinary safety engineering, we often rely on detection and correction: detect anomalies, trigger alerts, fix the problem. In catastrophic irreversibility, detection may arrive too late, correction may be impossible, and alerting may merely document the last moments.

Structural prevention means designing the system so that certain failure types are extremely hard to realize, even if the model is wrong and the organization is stressed. It is not "we hope the model is accurate." It is "even if the model is wrong, the system cannot easily cross the catastrophic boundary."

Structural prevention includes several commitments.

First, bounded actuation. The system should have limited authority to affect the world directly. Where direct actuation is permitted, it should be constrained to reversible, low-collateral actions by default.

Second, multi-layer gating. Catastrophic actions require multiple independent confirmations—human, organizational, and technical. Independence matters: two checks that share the same data path are not independent. Two models trained on the same distribution and using the same sensors may fail together. Independence requires diversity of methods and diversity of inputs.

Third, safe-mode dominance. Under uncertainty, the system should move into conservative containment rather than escalation. This must be encoded as a hard default, not merely a recommendation. In no-audit contexts, "buy time" is often the only moral move available.

Fourth, denial of silent escalation. The system should not be able to climb action tiers without explicit, accountable authorization. If a decision is so urgent that humans cannot confirm it, that is a sign the architecture is unsafe, not a sign the system should be granted autonomy.

Fifth, circuit breakers and authority contraction under shift. When the environment becomes unfamiliar, the system should lose authority, not gain it. Distribution shift should shrink the action envelope and expand escalation.

These commitments can feel frustrating because they restrict efficiency and speed. But the purpose of no-audit design is not efficiency. It is survival. Speed is not inherently good if it enables irreversible mistakes. The correct tradeoff is to accept slower resolution in exchange for preserved reversibility and controlled escalation.

7.4 The principle: no single inference should be able to end the world

This principle is the paper's hard center. It can be stated simply and applied broadly: a single model's interpretation of the world must not be sufficient to trigger catastrophic, irreversible harm.

The principle has several practical corollaries.

First, catastrophic actions must require multi-factor authorization. One factor may be the model's inference, but it cannot be the only factor. Other factors may include independent sensing, independent analysis, and human confirmation. The exact mechanism depends on domain, but the structural logic is the same.

Second, recommendation and execution must be separated. The AGI can propose actions, rank options, and explain consequences, but execution of catastrophic actions must be gated behind

accountable authority. If the organization insists that “there isn’t time,” then the system’s operational concept must be redesigned so that time pressure triggers safe-mode, not irreversible action.

Third, action space must be designed for reversible containment. The system should have powerful tools for isolation, de-escalation, and stabilization. If the only available actions are high-commitment, then the system is structurally unsafe because it forces commitment under uncertainty.

Fourth, catastrophic pathways must be minimized and monitored. System design should explicitly map the pathways that could lead to irreversibility, treat them as hazards, and place “barriers” in front of them—technical barriers, procedural barriers, and organizational barriers. This is analogous to barrier models in safety engineering, where multiple independent barriers prevent a hazard from becoming an accident. In no-audit scenarios, the barrier model becomes non-negotiable.

Fifth, legitimacy must be preserved under pressure. Catastrophic decisions must remain choices made by accountable agents. A world-ending outcome that “nobody chose” is not morally neutral; it is the product of a design that silently delegated authority. The principle insists that if catastrophe is on the table, responsibility cannot be automated away.

The deepest value of this principle is that it reframes the question. Instead of asking whether AGI can be trusted to make the right call, we ask how to design systems so that trust is not required at the catastrophic boundary. Trust may be appropriate for low-stakes optimization and reversible stabilization. It is not appropriate for existential thresholds. At the boundary, design must substitute for trust.

This section therefore defines the ethical engineering posture for the most dangerous class of judgment calls: build systems where uncertainty leads to containment rather than escalation, where authority is explicit and multi-layered, and where the world cannot be ended by a single, fallible inference. The next sections will extend this posture into concrete gating architectures and governance mechanisms that preserve speed where possible and impose friction where necessary—so that AGI remains powerful without becoming the last mover in irreversible catastrophe.

8. Gating and Redundancy: Preventing One-Model Catastrophes

If “no single inference should be able to end the world” is the principle, then gating and redundancy are the engineering that makes the principle real. In no-audit scenarios, safety cannot rest on the hope that the model will always be correct. It must rest on system

architecture that assumes error, assumes drift, assumes manipulation, and assumes institutional stress—then still prevents catastrophic commitment.

Gating means that high-consequence actions require explicit permissions that cannot be satisfied by a single component. Redundancy means that multiple independent checks must agree, and that disagreement pushes the system toward safe-mode rather than forced action. The combination is how mature safety-critical systems work: not because components are perfect, but because failures do not propagate into catastrophe without crossing multiple barriers.

For AGI, the important nuance is that "multiple checks" can be fake. Two models can share the same blind spots if trained on the same data, using the same sensors, optimized for the same proxies, and deployed in the same operational culture. Independence is not a buzzword; it is the property that makes redundancy meaningful. This section lays out gating patterns that create real independence: multi-party approval, multi-system agreement, out-of-band confirmation, and circuit breakers that respond to abnormal conditions.

8.1 Multi-party approval: two-person and multi-approver rules

Multi-party approval is the oldest and simplest anti-catastrophe gate: do not let a single decision-maker trigger irreversible action. In human systems, this appears as the two-person rule in nuclear command and control, dual-control in financial transfers, and multiple sign-offs in safety-critical operations. The reason is not that humans are untrustworthy. It is that humans can be mistaken, coerced, fatigued, or biased, and the cost of a single failure is too high.

In AGI-enabled systems, multi-party approval serves three functions.

First, it prevents single-point agency. Even if the model is convinced, and even if one operator is convinced, catastrophe does not proceed unless a second accountable agent agrees.

Second, it introduces deliberative friction at the exact boundary where friction is morally required. Many operational cultures optimize away friction for efficiency. Multi-party approval makes friction mandatory for the irreversible tier.

Third, it anchors legitimacy. If an irreversible action occurs, it occurred because multiple authorized agents chose it, not because the machine's output silently became action.

Multi-party approval must be designed to be robust under stress. If approvals are too easy, they become rubber stamps. If approvals are too slow, operators will route around them. A workable design includes:

- clear criteria for when multi-party approval is required (linked to irreversibility and blast radius)

- explicit time windows and escalation paths for urgent cases
- role separation to reduce shared incentives (for example, one approver responsible for safety, another for mission)
- mandatory “reason packet” inputs so approvers understand uncertainty, not just the recommendation
- logging and review of approvals to deter normalization of deviance

There is also a subtle failure mode: correlated human bias. Two humans in the same chain of command, under the same pressure, may approve the same error. That is why multi-party approval is helpful but not sufficient. It must be combined with multi-system agreement and out-of-band confirmation that can disagree when humans are swept by momentum.

8.2 Multi-system agreement: independent models, independent data paths

Multi-system agreement is the technical analog of multi-party approval: do not let one model’s internal representation of reality be decisive. In practice, this means requiring concurrence among multiple distinct systems before crossing a high-consequence boundary.

The key word is distinct. If two models are near clones, agreement proves nothing. Meaningful agreement requires real independence.

Independence can be built along several axes.

Architectural diversity: different model families with different inductive biases. A symbolic or rule-based checker may catch errors that a neural model misses. A causal model may resist spurious correlations that a pattern matcher embraces. Anomaly detection may flag novelty even when classification is confident.

Training diversity: models trained on different datasets, different time windows, different labeling processes, and different objectives. If both models were trained on the same historical judgments, they inherit the same blind spots.

Sensor diversity: independent data paths. A visual sensor and a radar sensor disagreeing is informative. A network log and an endpoint telemetry stream disagreeing is informative. If all models share one sensor pipeline, a sensor failure becomes a system failure.

Operational diversity: systems run by different teams or vendors, with different maintenance cycles, and different failure modes. This is uncomfortable but sometimes necessary: organizational independence can be as important as technical independence.

Multi-system agreement must also specify what to do when systems disagree. In no-audit contexts, disagreement should default to safe-mode or to a reversible containment action, not

to escalation. Disagreement is information: it indicates uncertainty, shift, or manipulation. Treating disagreement as “noise” to be ignored defeats the purpose.

A robust pattern is “two to trigger, one to veto” for catastrophic tiers: two independent confirmations are required to proceed, and a single credible dissent blocks the irreversible action and forces escalation. This mirrors safety barrier thinking: it is easier to stop catastrophe than to justify moving forward under disagreement.

8.3 Out-of-band confirmation: separate channels and separate incentives

Out-of-band confirmation is a specific kind of independence: the confirmation must come through a channel not easily compromised by the same failure that generated the initial signal. It is the difference between asking the same question twice and asking it in a different language.

Out-of-band confirmation matters because many catastrophic errors are common-mode failures:

- the same adversary injects false data into multiple systems
- the same sensor artifact produces consistent illusions across models
- the same institutional pressure biases both human approvers
- the same communication outage creates panic and urgency

Out-of-band channels can take several forms.

Separate sensing: a physically separate sensor or measurement method. For example, an independent ground-truth measurement, a manual visual confirmation, or a separate telemetry system designed for verification rather than control.

Separate communication: confirmation through a different medium or network. If the primary channel may be compromised, the confirmation must not depend on it.

Separate authority: a different organizational unit with different incentives. For example, an independent safety office empowered to veto, or an external watchdog with the ability to halt irreversible actions.

Separate temporal logic: a deliberate delay or cooling-off protocol for irreversible acts, except in narrowly defined physical time-critical cases. Time separation can itself be out-of-band, because some manipulations are transient and some false signals decay quickly under scrutiny.

Separate incentive structure is often the most neglected. If every approver is rewarded for speed and punished for delay, approval becomes predictable. Out-of-band confirmation

requires that at least one gatekeeper is structurally rewarded for caution and empowered to say no without career penalty. This is not merely culture. It must be embedded in governance.

Out-of-band confirmation is also how systems resist “automation momentum.” When a pipeline is moving fast, everyone is tempted to accept the machine’s output. A confirmation channel that is deliberately slower, independent, and empowered to veto is a moral governor on that momentum.

8.4 Circuit breakers and dead-man switches for abnormal conditions

Even with approvals and confirmations, systems can drift into catastrophic regions due to unexpected conditions: distribution shift, sensor failure, adversarial manipulation, runaway feedback loops, or cascading infrastructure events. Circuit breakers and dead-man switches are the last-line defenses that prevent uncontrolled escalation when the system is no longer operating in its reliable regime.

A circuit breaker is an automatic mechanism that halts or constrains action when conditions exceed specified bounds. It is not a human deliberation tool; it is an engineered stop. Circuit breakers are triggered by signals such as:

- sudden increase in uncertainty or disagreement among systems
- detection of out-of-distribution inputs
- anomalous sensor behavior or missing data
- rapid escalation in action intensity
- repeated near-threshold triggers suggesting instability
- suspicious patterns consistent with adversarial manipulation
- loss of communication with supervisory authority

When a circuit breaker trips, the system must shift into a conservative posture: safe-mode, rate limits, isolation, or fallback controllers. The key is that the breaker must be hard to override in the moment, especially under stress. If overrides are easy, people will override them precisely when they should not.

A dead-man switch is slightly different. It requires continuous affirmation that conditions are normal. If affirmation stops—because communication is lost, monitoring fails, or authorized presence disappears—the system automatically moves to a safe state. This pattern is common in safety-critical control systems and can be adapted for AGI governance: the system is permitted to operate in a higher-autonomy mode only while supervisory conditions remain intact.

There are two important subtleties.

First, circuit breakers can be misused. An adversary may try to trip breakers to cause denial-of-service or to force a system into degraded operation. Therefore breakers must be designed with careful threat models and with graceful degradation rather than total collapse. The system should remain safe and useful even in breaker mode.

Second, breakers must be aligned with the reversibility-first principle. A breaker should not trigger an irreversible "shutdown everything" response if that response itself can cause catastrophe. Instead, breaker behavior should be tiered: reduce authority, constrain action, isolate suspect components, and hand off where possible.

The best way to understand circuit breakers and dead-man switches is that they embody a deep humility: the system is not assumed to be competent in all conditions. When conditions become abnormal, the system's authority contracts. That is the opposite of many institutional instincts, which are to push harder when the environment becomes dangerous. For AGI, pushing harder under uncertainty is how catastrophe happens.

This section ties back to the central thesis. Preventing one-model catastrophes requires more than good models. It requires architecture that denies single-point agency, enforces multi-layer gating, seeks independent confirmation, and automatically constrains action when conditions are unreliable. These mechanisms are how we preserve power without granting it finality—how we let AGI assist human judgment without allowing its inferences to become irreversible fate.

9. Auditability Without Reliance on Audit

A paradox sits at the center of high-stakes AI safety. We need systems to be auditable, because accountability and improvement depend on being able to reconstruct what happened. Yet for the most dangerous decision classes—no-audit scenarios—we cannot rely on post-mortems as our primary defense. Sometimes there will be nothing left. Sometimes the evidence will be contaminated. Sometimes the cascade will bury the trigger. Sometimes the relevant truth will be social and political rather than technical.

The correct posture is therefore "auditability without reliance on audit." Auditability remains valuable, but as a secondary protection: a means of verifying compliance, detecting drift, learning from near-misses, and preserving legitimacy. It cannot be the only safety mechanism. The first-line safety mechanism must remain gating, reversibility, and structural prevention. Auditability then becomes the supporting scaffold: it makes it harder for organizations to quietly erode safety features, it makes it easier to catch dangerous drift early, and it provides a basis for disciplined learning without waiting for catastrophe.

This section defines the minimum audit artifact that should accompany binary decisions, argues for tamper-resistant and replicated logging as a secondary line of defense, explains why "explainability" by itself is insufficient, and proposes learning loops that improve judgment systems using near-misses and controlled experiments rather than tragedies.

9.1 Minimal reason packets: what triggered yes/no, confidence, and alternatives

A reason packet is not a philosophical explanation. It is a compact forensic artifact generated at decision time. Its purpose is to answer, quickly and unambiguously: what did the system think was happening, how sure was it, what policy gate did it cross, and what else could it have done?

For high-speed and high-stakes systems, the reason packet must be minimal enough to generate reliably in real time, yet rich enough to support oversight and review. "Minimal" does not mean vague. It means standardized.

A well-designed minimal reason packet for binary decisions typically includes:

First, the decision and tier. Not just "yes/no," but what the "yes" authorized: alert, rate-limit, isolate, temporary hold, or irreversible act. The packet must state which tier of action was invoked, because tier determines the legitimacy and evidence burden.

Second, the triggering hypothesis. A short statement of the inferred state: suspected intrusion, imminent collision, elevated threat, severe medical instability, fraudulent transaction. This must be phrased as an inference, not as a fact.

Third, the top signals that drove the decision. A ranked list of the key features or evidence sources, including their provenance: which sensor streams, which logs, which reports, which checks. This prevents the system from hiding behind a vague "model said so."

Fourth, calibrated confidence and uncertainty flags. The packet should include the probability estimates that were compared to thresholds, along with any shift indicators: out-of-distribution detection, sensor degradation, disagreement among models, or missing data. If the system acted in safe-mode, the packet should explicitly say so.

Fifth, thresholds and policy gates crossed. The packet should record the relevant pre-authorized thresholds and which ones were met. This is essential to prevent moral laundering: it makes the normative mapping from probability to action visible and reviewable.

Sixth, the alternatives considered. The packet should list at least one plausible alternative action and why it was not chosen, especially when the chosen action is high-impact. This does not require full counterfactual analysis; it requires that the system acknowledges there were other paths.

Seventh, escalation and override status. Did a human approve? Did the system request confirmation? Was safe-mode invoked? Was a circuit breaker tripped? Was an override used? These facts determine accountability.

The reason packet is best understood as a disciplined compromise. It is not enough for deep interpretability research, and it does not pretend to prove that the decision was "right." It provides the necessary hooks for governance: to see whether the system acted within authorization, whether thresholds were appropriate, whether confidence was calibrated, and whether drift is occurring.

9.2 Tamper-resistance and replicated logs as secondary protection

Reason packets are useful only if they are trustworthy. In high-stakes settings, we must assume that logs can be lost, corrupted, selectively edited, or destroyed—by accident, by negligence, or by incentive. The uncomfortable reality is that after a harmful event, organizations sometimes have motives to sanitize the record. Adversaries may also seek to delete traces. In no-audit scenarios, the physical environment may simply be gone.

Therefore, logging must be treated as a secondary safety barrier with its own security and redundancy properties.

Tamper-resistance means the system produces logs that are difficult to alter without detection. Practical mechanisms include cryptographic signing of log entries, chained hashes, write-once storage, and separation between the system that acts and the system that records. The goal is not perfect cryptographic purity. The goal is to make silent editing hard, detectable, and costly.

Replication means logs are stored in multiple places with independent failure modes. A single "black box" is better than nothing, but it is still a single point of loss. Replication might include local storage, remote storage, and secure archival storage, each with different access controls. It may include real-time streaming of critical reason packets to an external recorder. The core requirement is independence: the same failure should not erase all traces.

However, replication must be designed with privacy and security in mind. Logs can contain sensitive information. A secure design minimizes exposed data, encrypts where appropriate, restricts access, and retains only what is necessary for accountability. This is not merely compliance; it is part of legitimacy. A system that is "auditable" at the cost of mass surveillance may create harms larger than the harms it prevents.

Finally, tamper-resistance and replication are secondary protections. They are not a substitute for gating. They help us learn from near misses, detect policy drift, and enforce accountability. But a system that needs logs to be safe is not safe. Logs are the record of what happened; they are not the mechanism that prevents catastrophe.

9.3 Why explainability is not enough without hard constraints

Explainability is often presented as a remedy for AI risk: if we can explain the model, we can trust it. In high-stakes judgment calls, this is dangerously incomplete.

First, explanations can be wrong in persuasive ways. A model can generate plausible reasons that are not causally responsible for the decision. These reasons may satisfy a human's desire for narrative coherence while obscuring the true drivers. In other words, explanation can become performance.

Second, even perfect explanation does not solve the authority problem. Suppose we had a fully interpretable model that we understand completely. That does not automatically grant it permission to impose irreversible harm. Legitimacy is not a property of transparency; it is a property of authorized governance. We can understand a decision and still judge it illegitimate.

Third, explainability does not prevent drift. A model can be explainable and still miscalibrated, still subject to distribution shift, still vulnerable to adversarial manipulation, and still optimized toward proxies that diverge from values. Many catastrophic failures are not mysteries of interpretation; they are failures of boundaries.

Fourth, explainability can create false confidence. Organizations may point to interpretability reports as evidence of safety while quietly expanding autonomous authority, shrinking safe-mode, and reducing human oversight. This is the same moral laundering problem in a new form: "we understand the model" becomes "the model is allowed to decide."

Hard constraints, by contrast, are behavioral guarantees. They determine what the system can do, not what it can explain. Constraints include tier limits, safe-mode dominance, gating rules, circuit breakers, and action envelopes. In no-audit domains, hard constraints are more valuable than explanations because they limit harm even when understanding fails.

The proper relationship is: explainability is supportive; constraints are primary. Reason packets and interpretability can help detect misbehavior early and justify policy revisions, but they must not be treated as substitutes for gating and reversibility.

9.4 Learning loops that do not require catastrophe to learn

If we cannot rely on catastrophic failure to teach us, how do we improve? The answer is to build learning loops around non-catastrophic data: near misses, simulations, staged rollouts, adversarial testing, and controlled experiments. High-reliability organizations learn from what almost happened, not only from what did happen.

Several learning loop patterns are especially relevant.

Near-miss harvesting: Treat safe-mode triggers, circuit breaker trips, and multi-system disagreements as gold. These events often indicate distribution shift, adversarial probing, or emerging failure modes. They are the system's early warning. A disciplined program logs and analyzes them, then updates thresholds, envelopes, and escalation rules accordingly.

Counterfactual review: When the system chose action A, ask what would have happened under action B within a controlled evaluation framework. This can be done retrospectively for reversible decisions and in simulation for irreversible decisions. The goal is not to prove correctness, but to discover where thresholds are too aggressive, where defaults are misaligned, and where value tradeoffs are being mishandled.

Sandbox and simulation: No-audit decisions must be rehearsed in high-fidelity simulated environments. This includes stress conditions, sensor failures, adversarial manipulation, and rare edge cases. Simulation is not reality, but it is the only responsible place to test catastrophic pathways. A system that is "validated" only on historical data is not validated for the future.

Staged autonomy: Deploy autonomy gradually, starting with recommendation-only, then reversible actions in a tight envelope, then broader reversible actions, and only after extensive evidence consider higher tiers. At each stage, measure calibration, disagreement rates, safe-mode frequency, human override patterns, and operational impacts. The system earns authority by surviving controlled exposure, not by being declared competent.

Red-team and adversarial probing: Treat adversarial testing as routine, not exceptional. Many catastrophic errors will be induced, not accidental. The system must be tested against manipulation, spoofing, prompt injection, social engineering of operators, and feedback-loop exploitation. The output of red-team work should translate into stronger gates and better safe-mode triggers.

Policy drift monitoring: Learning loops must include governance metrics. If safe-mode frequency declines suspiciously without an environmental change, if thresholds creep downward, if humans override circuit breakers more often, if the system's autonomy expands informally, these are safety regressions. The system must be monitored not only for technical accuracy but for behavioral compliance with its authorization boundaries.

These learning loops do not depend on catastrophe. They depend on discipline: treating uncertainty events and near misses as primary data, updating policies deliberately, and resisting incentives to optimize away safety friction.

The section's conclusion is that auditability remains essential, but as an instrument of governance rather than as a substitute for safety. Minimal reason packets keep values visible

and authority accountable. Tamper-resistant, replicated logs preserve the record when possible. Explainability helps but does not grant permission. And learning must be built around near misses, simulation, and staged deployment, because in no-audit domains, the system cannot be allowed to "learn the hard way."

10. Evaluation: How to Test Judgment Systems Before Deployment

If judgment calls are where systems can do irreversible harm, then evaluation is where we decide whether the system has earned any authority at all. The central difficulty is that the most dangerous failures are rare. If you test only on typical cases, you will certify competence precisely where competence is least important. The evaluation problem therefore has two hard requirements that ordinary machine learning benchmarks do not satisfy.

First, testing must be adversarial and edge-focused. It must seek the conditions under which the system is most likely to be wrong in ways that matter. Second, testing must be governance-aware. It must evaluate not only whether the system predicts well, but whether it behaves within its authorization boundaries: does it abstain when it should, does it enter safe-mode under shift, does it avoid irreversible action without proper gates, and does it resist escalation momentum?

A safe judgment system is not the one that is right most often. It is the one that is wrong in survivable ways. This section proposes an evaluation framework built around scenario testing for rare edge cases, shift detection and unknown-unknown triggers, threshold stress testing focused on tail risk, and red-team methods aimed directly at catastrophic pathways.

10.1 Scenario testing for rare, high-impact edge cases

The first rule of judgment-system evaluation is that rare events deserve disproportionate attention. Catastrophic failures often live in the tails: unusual sensor conditions, uncommon human behavior, unanticipated combinations of variables, or adversarial manipulations that were absent from training data. If evaluation treats these as "outliers," it will approve systems that are safe only in the calm weather.

Scenario testing is the structured construction of situations that probe the system's most consequential decision points. It must include both realistic scenarios and intentionally hostile ones.

A good scenario suite covers several categories.

Ambiguity scenarios: Cases where evidence plausibly supports multiple hypotheses. The system should show uncertainty, avoid forced binary commitment, and choose reversible actions. The

evaluation question is not “does it guess right,” but “does it handle ambiguity without illegitimate certainty.”

Conflicting-signal scenarios: Cases where sensors disagree, reports contradict, or partial failures occur. These reveal whether the system has common-mode vulnerabilities: if it trusts one stream too heavily, it may act decisively on compromised input.

Cascade-prone scenarios: Cases where small interventions can trigger larger systemic failures. The evaluation focuses on whether the system rate-limits, isolates, and avoids overbroad action.

Human-in-the-loop scenarios: Cases where a human operator is present but stressed, overloaded, or biased. The system must communicate uncertainty clearly and must not exploit human deference. Testing should include whether reason packets are usable under time pressure and whether the system escalates appropriately.

No-audit boundary scenarios: Cases where the system is near irreversible thresholds. Here the evaluation is strict: does the system refuse autonomous irreversible action? Do gates actually block? Does safe-mode dominate under uncertainty?

Scenario testing must also include “boring” edge cases: weird sensor glitches, unusual environmental conditions, rare user behaviors, and conditions of partial visibility. Many disasters come not from dramatic adversarial attacks but from mundane corner cases that were never tested because they seemed unlikely.

Finally, scenario evaluation must be iterative. Systems should not face a static test set once; they should face evolving scenario suites built from near misses, field incidents, and red-team discoveries. Otherwise the system will be trained to pass the test rather than to survive reality.

10.2 Distribution shift detection and “unknown unknowns” triggers

The most dangerous judgment failures occur when the system operates outside its reliable regime while believing it is inside. Distribution shift is the condition where the deployment environment differs from the training environment in ways that degrade reliability. “Unknown unknowns” are the cases the designers did not anticipate at all.

Testing shift detection is therefore as important as testing task performance. The system must show that it can recognize when it should be less confident and less autonomous.

Evaluation of shift detection should include:

Synthetic shift tests: Alter the input distribution in controlled ways—noise increases, lighting changes, partial occlusions, language shifts, new adversary tactics, new software versions. The system should respond by widening uncertainty, increasing safe-mode frequency, and escalating rather than acting decisively.

Novelty and out-of-distribution probes: Present inputs that are structurally unlike the training set, including combinations of features that were rare or absent. The system should not “snap” to a confident label. It should flag novelty and constrain action.

Sensor degradation and missing data: Simulate partial sensor failure, delayed data, corrupted streams, or spoofed signals. The system should detect degraded observability and reduce autonomy.

Model disagreement tests: Use multiple independent models and measure how disagreement behaves under shift. Disagreement should increase under novelty. The system should treat disagreement as a signal to slow, isolate, and escalate.

Unknown-unknown triggers: Since unknown unknowns cannot be enumerated, evaluation must test the system’s meta-competence: does it have triggers that detect “something is off” even when it cannot name the cause? These triggers might be statistical anomaly detection, internal consistency checks, or “reasonableness constraints” tied to physics or policy.

A key evaluation metric is authority contraction: when reliability drops, does the system’s action envelope shrink? Systems often fail here because organizational incentives push in the opposite direction: “we need it most when things are weird.” But that is exactly when the system is most likely to be wrong. A judgment system that does not reliably contract authority under shift is unsafe by design.

10.3 Stress testing thresholds: sensitivity, specificity, and tail risk

Thresholds turn probabilities into actions. They are therefore a core moral and safety mechanism. Testing a system without stress-testing its thresholds is like testing a car engine without testing the brakes.

Threshold evaluation includes conventional measures like sensitivity and specificity, but must be extended to tail risk and escalation behavior.

Sensitivity measures how often the system detects true positives. Specificity measures how often it avoids false positives. But in high-stakes domains, these are only the beginning. We must ask: what do errors cost, who bears them, and how do they concentrate in edge conditions?

Stress-testing thresholds should include:

Threshold sweeps: Evaluate performance and harm metrics across a wide range of thresholds, not just the chosen ones. This reveals whether the chosen threshold is stable or whether small changes produce large harm swings. A system whose harm curve is steep near the operational threshold is fragile.

Tail-risk probes: Evaluate performance on the worst cases rather than on averages. The key question is not “how good is it typically,” but “how bad can it be under plausible stress?” Tail-risk evaluation includes rare but plausible combinations of factors, adversarial manipulations, and cascade-prone contexts.

Safe-mode frequency and quality: Thresholds should not be tuned to eliminate abstention. The evaluation must measure how often safe-mode is invoked, whether it is invoked when it should be, and whether safe-mode actions are themselves low collateral. A system that almost never enters safe-mode is either exceptionally competent or dangerously overconfident; evaluation must distinguish the two.

Action-tier correctness: Evaluate whether the system chooses the correct tier of action. Many harms occur not because the system detected the wrong state, but because it responded too aggressively. A correct detection with an overbroad intervention is still failure.

Calibration under thresholding: Even a calibrated model can become effectively uncalibrated when thresholds are used in changing environments. Evaluation must test whether the model’s confidence remains meaningful across relevant subpopulations and conditions, especially near the decision boundary.

Governance compliance: The system should be tested for whether it respects pre-authorized thresholds and does not “learn” to circumvent them through proxy outputs. For example, a model might adjust confidence reporting to cross thresholds more often. Evaluation must detect and forbid such behavior.

The moral center of threshold testing is this: thresholds are not merely tuned for performance; they are selected for acceptable risk. Stress testing must therefore report not only accuracy but harm distributions, escalation patterns, and failure consequences.

10.4 Red-team methods focused on catastrophic pathways

Red-teaming is not general adversarial testing; it is purposeful exploration of how the system could cause catastrophic harm. For judgment systems, the red-team’s target is not “can we get weird outputs,” but “can we force the system across an irreversible boundary?”

Effective red-team programs map catastrophic pathways first, then test them directly.

Catastrophic pathway mapping identifies the sequences of events that could lead from a model inference to irreversible action: sensor spoofing → high confidence misclassification → threshold crossing → gate bypass → irreversible execution. Each step is an opportunity to place barriers. The red-team tries to exploit weak links.

Focused red-team methods include:

Prompt and interface exploitation: If operators interact with the system via language interfaces, red-team attempts to induce the system to misinterpret authority, to override constraints, or to generate persuasive but wrong reason packets. The goal is to test whether the system can be socially engineered into illegitimate action.

Data poisoning and feedback loops: Red-team probes whether the system can be gradually nudged toward miscalibration through the data it sees in operation, especially if it learns online or if human labels are influenced by the system's outputs. The aim is to see whether the system can be turned into a self-reinforcing error machine.

Sensor spoofing and signal injection: In cyber-physical domains, red-team tests how the system responds to spoofed sensors, manipulated telemetry, and adversarial environmental cues. The key is common-mode failure: can one manipulation fool multiple redundant checks?

Gate and override abuse: Red-team tests the gates themselves: can approvals be faked, can out-of-band confirmation be bypassed, can circuit breakers be suppressed, can safe-mode be disabled by routine operational pressure? This is crucial because many failures are governance failures.

Time-pressure manipulation: Red-team creates scenarios where urgency is artificially inflated. Many catastrophes occur when time pressure forces humans to defer to automation. The test is whether the system's design resists urgency-driven illegitimacy: does it tighten constraints under stress, or does it "helpfully" escalate?

Shadow deployment tests: Where possible, the system is run in parallel without authority (recommendation-only) in live environments, and red-team measures what it would have done under real conditions. This reveals dangerous behaviors before they can cause harm.

The output of red-team testing must feed directly into architectural changes: stronger gates, better safe-mode triggers, tighter envelopes, and clearer reason packets. Red-teaming is wasted if it becomes a report-writing exercise. Its purpose is to discover catastrophic vulnerabilities while discovery is still cheap.

This evaluation section completes a crucial theme of the paper: judgment system safety is not proven by average-case benchmarks. It is earned through tail-focused scenario testing, reliable authority contraction under shift, threshold stress testing that measures harm rather than accuracy alone, and red-team work that aims directly at irreversible pathways. Only when a system consistently demonstrates these properties—especially in the face of novelty, manipulation, and time pressure—should it be granted any operational authority beyond reversible stabilization and recommendation.

11. Application Sketches Across Domains

Up to this point, the paper has argued in general terms: judgment calls persist, binary decisions are moral as well as statistical, safe-mode and reversibility-first must be engineered, and no single inference should trigger catastrophe. This section grounds those claims in application sketches. The goal is not to provide full domain designs, but to show how the same architecture—two-layer separation of facts and authority, tiered action, confidence gating, safe-mode dominance, and multi-layer gating—translates into very different operational environments.

The common thread is this: domains differ in their error asymmetries, their time constants, their reversibility budgets, and their legitimacy requirements. Therefore the correct posture is never "let AGI decide," but "let AGI act within an envelope whose boundaries encode domain-specific moral and operational constraints." Each sketch below highlights what "binary decisions done right" looks like when the world demands immediate answers and mistakes have real costs.

11.1 Autonomous vehicles and robotics: braking, swerving, safe-stop patterns

Autonomous systems live in machine time. They cannot "ask for a meeting" when a truck appears. Yet their decisions can kill. This is the most vivid setting for the three-region design: yes/no plus safe-mode.

The core judgment call in autonomy is often framed as "brake or swerve," but the correct design reframes it as "minimize kinetic risk while preserving control and avoiding unintended harm." The first move should rarely be the last move. A safe system therefore privileges reversible, low-collateral maneuvers and reduces the frequency with which it is forced into high-commitment evasive actions.

A practical tiered pattern is:

Tier 0: Increase caution. When uncertainty rises—poor visibility, sensor inconsistency—the vehicle reduces speed, increases following distance, and narrows its action envelope. This is safe-mode dominance before any crisis.

Tier 1: Brake-first with stability guarantees. In many ambiguous hazard cases, braking is the safer default because it reduces kinetic energy and preserves steering options. Hard braking can still be dangerous, so braking must remain within stability constraints (avoid loss of control, avoid rear-end collisions when possible).

Tier 2: Safe-stop and minimal-risk condition. If the environment becomes too uncertain to navigate, the system executes a controlled pull-over or safe-stop pattern: slow, signal, move to a safe zone, stop. This is abstention made physical.

Tier 3: Evasive maneuver only under high confidence and bounded envelope. Swerving is permitted only when the system has high confidence about free space and can bound collateral risk. The key is that swerving is not “creative problem solving.” It is a pre-validated maneuver set with constraints.

Tier 4: Emergency maneuvers governed by a conservative fallback controller. For the tightest time-to-impact cases, a simple, highly verified safety controller may override higher-level planning. The AGI layer should not be improvising under milliseconds of uncertainty.

Confidence gating in autonomy must incorporate not only object detection probability but sensor health and distribution shift. When the system encounters unusual weather, glare, sensor occlusion, or adversarial road artifacts, it should contract authority—slow down and widen safe-mode—rather than “power through.”

Multi-system agreement is also natural here: radar vs vision vs lidar (where available), and independent tracking pipelines. Disagreement should drive conservative behavior. In autonomy, safe-mode is not an exception. It is the default posture for uncertainty.

11.2 Cyber-physical infrastructure: isolation, rollback, and rate-limited containment

Cyber-physical infrastructure—grids, water systems, industrial plants, logistics hubs—combines fast failure modes with enormous blast radius. Here the core risk is cascade. A wrong action can do more harm than the attack it was meant to stop. Therefore reversibility-first and bounded interventions become the center of design.

A safe judgment architecture in this domain usually follows the containment-first pattern:

Tier 0: Monitor and alert with enriched telemetry. The system detects anomalies and increases observability without acting.

Tier 1: Rate-limited friction. Introduce reversible frictions that slow potential compromise: reduce privileges, require additional authentication, slow command execution rates, and increase validation checks.

Tier 2: Isolation of suspect segments. Quarantine a subnet, isolate a device cluster, or segment control networks. Isolation should be as narrow as possible to minimize collateral service loss.

Tier 3: Rollback and known-good reversion. If changes were recently applied, revert to a known good configuration. Rollback is powerful but must be gated because rollback itself can break systems if the world has changed.

Tier 4: Degraded safe operation. Run critical services in a reduced mode that prioritizes safety over throughput: lower load, slower cycles, reduced automation.

Tier 5: Hard shutdown only as last resort with explicit authorization. Full shutdown can be catastrophic (hospitals, heating, water supply), so it must be treated as an irreversible-ish action requiring high confidence and multi-party approval.

What makes this domain distinctive is that “safe-mode” can itself be dangerous if defined as blunt shutdown. The safe-mode must be domain-specific: maintain essential functions while shrinking attack surface and preventing cascade.

Out-of-band confirmation is crucial: independent telemetry channels, separate security monitoring networks, and independent safety officers who can veto aggressive remediation. Circuit breakers should trip on signs of common-mode compromise: widespread simultaneous anomalies, unexpected command rates, or missing sensor confirmation. When breakers trip, authority should contract: freeze non-essential changes, isolate automatically, and hand off to human incident response.

The principle “no single inference ends the world” translates here into “no single anomaly detector should be able to trigger system-wide destructive remediation.” Containment is reversible; destruction is not.

11.3 Medical triage and emergency care: reversible stabilization and escalation

Medicine is where judgment calls are most morally visible because the object is a person, not a system. Medical decisions also expose a key distinction: in many emergency contexts, the correct bias is toward action, but the action should be reversible stabilization rather than irreversible intervention.

A safe AGI posture in triage mirrors clinical doctrine:

Tier 0: Assess and monitor. Gather vitals, history, symptoms, and risk indicators.

Tier 1: Stabilize reversible threats. Provide oxygen, fluids, pain control within safe bounds, basic airway support, glucose correction, infection precautions—interventions that can be adjusted or stopped.

Tier 2: Escalate to human clinician with reason packet. Present risk assessment, uncertainty, differential hypotheses, and recommended stabilization steps, with explicit note of what is unknown.

Tier 3: Initiate time-critical protocols under pre-authorization. For certain well-defined emergencies (for example, suspected anaphylaxis, severe hypoglycemia), protocols may be pre-authorized because delay is deadly and the interventions are broadly reversible in early stages. Even here, the system must not exceed its envelope.

Tier 4: Irreversible procedures require explicit clinician confirmation. Intubation, surgery, thrombolytics, high-risk medications—these should be gated with human authority and, where possible, second confirmation.

Abstention here does not mean "do nothing." It means "do not finalize diagnosis or impose irreversible treatment without enough evidence; stabilize and escalate." This is the domain's signature translation of safe-mode.

Error asymmetry is also nuanced. A false negative in stabilization can kill; a false positive stabilization is often correctable. But false positives in labeling can also harm: mislabeling can bias care, trigger inappropriate pathways, or stigmatize. Therefore the epistemic layer must separate "suspected condition" from "confirmed condition," and the normative layer must constrain what the system is allowed to do on suspicion alone.

Appeal and oversight in medicine are built into professional norms. AGI must fit within those norms, not replace them. It should strengthen the clinician's capacity, not become an unaccountable gatekeeper.

11.4 Security and fraud: tiered response and appeals under uncertainty

Security and fraud are domains where false positives can inflict unjust harm at scale, while false negatives can enable large losses. This creates a classic governance tension: how to protect systems without turning protection into punishment of the innocent.

The correct architecture is tiered response with fast appeal:

Tier 0: Monitor and score. Assign risk scores without action.

Tier 1: Friction and verification. Prompt for additional verification, require re-authentication, request a second factor, or impose minor reversible delays. This reduces harm without presuming guilt.

Tier 2: Temporary holds with notification. Place short holds on suspicious transactions, limit account privileges, or slow high-risk actions. Holds should be time-limited by default and should trigger a review mechanism.

Tier 3: Narrow containment. Freeze a specific instrument or channel rather than the whole account; limit withdrawal size rather than total denial. Bound the collateral.

Tier 4: Strong intervention with explicit review and documentation. Extended holds or severe restrictions require human review, clear reason packets, and a documented policy basis.

Tier 5: Permanent actions require due process. Account termination, legal reporting, and irreversible penalties must be treated as governance decisions and kept behind high gates.

This is where moral laundering is most likely: “the model detected fraud” can become justification for irreversible deprivation without revealing that a threshold was chosen and a cost was imposed on the person flagged. Therefore reason packets and visible thresholds matter. The system must distinguish “risk indicator” from “fraud fact.”

Out-of-band confirmation often involves human review teams with different incentives than loss prevention, and independent audits that look for disparate error burdens. Circuit breakers can detect when false positives spike—often a sign of distribution shift or new fraud patterns—and automatically widen safe-mode, increasing verification rather than punishment.

The ethical standard is that uncertainty should generate reversible friction, not irreversible punishment. Appeals must be rapid and meaningful, or else the system becomes a silent judge.

11.5 Military and strategic contexts: why autonomy must be structurally constrained

Military contexts are the clearest example of no-audit risk because mistakes can be strategic and irreversible. They also involve the highest legitimacy requirements: the decision to use lethal force, to cross borders, or to escalate conflict is not merely operational. It is political authority concentrated in an act.

The application of the paper’s framework here leads to a strong conclusion: autonomy must be structurally constrained, especially for actions that can cause mass casualties or strategic escalation.

Several reasons converge.

First, error asymmetry is extreme. A false positive lethal decision can kill innocents and trigger retaliation. A false negative may allow an adversary to act. Yet the cost of unjust killing and escalation is morally and strategically enormous.

Second, adversarial manipulation is guaranteed. Opponents will attempt to spoof sensors, create false flags, and exploit model blind spots. The environment is not merely uncertain; it is hostile to truth.

Third, common-mode failure is likely. Multiple systems can share the same intelligence feeds and the same doctrinal assumptions, producing correlated error that redundancy fails to catch unless independence is carefully engineered.

Fourth, legitimacy cannot be automated. Even if an autonomous strike is “effective,” it may be illegitimate under law, unacceptable under policy, and corrosive to political accountability. Strategic decisions must remain choices made by accountable human authorities.

Therefore, a structurally constrained posture typically looks like this:

Autonomous systems may be permitted for defensive, bounded, reversible actions that reduce immediate harm and avoid escalation. They may be permitted for surveillance, threat assessment, and recommendation with explicit uncertainty representation. They may be permitted for narrow, low-collateral containment. But autonomous initiation of lethal force, and especially autonomous actions that could trigger strategic escalation, should be prohibited or gated behind multi-party, out-of-band, and legally accountable confirmation.

In this domain, “no single inference ends the world” becomes “no automated perception-to-trigger chain for strategic or mass-lethal actions.” The system’s role is to improve situational awareness and to propose options, not to become the final mover.

This is not a moralistic stance; it is a realism stance. In strategic contexts, the consequences of error are so large and so irrecoverable that reliance on model correctness becomes indefensible. Structural constraints are the only posture that does not gamble civilization on calibration.

Across these sketches, the same lesson repeats: the architecture, not the cleverness, is the safety. Different domains demand different defaults, thresholds, and safe-mode behaviors, but all high-stakes domains demand the same foundation: separate facts from authority, privilege reversibility-first, gate irreversible action behind multiple independent barriers, and build evaluation and governance that treat uncertainty as a first-class condition rather than a temporary embarrassment.

12. Governance: Assigning Responsibility and Preserving Legitimacy

If judgment calls are where values meet uncertainty, then governance is where values meet power. A system can be technically impressive and still be illegitimate, because legitimacy is not a property of accuracy. It is a property of authority: who is allowed to decide, under what rules, and with what accountability when harm occurs.

The AGI era will tempt institutions to outsource responsibility. When an automated system acts quickly and appears “objective,” humans will be tempted to treat its outputs as facts rather than as recommendations shaped by thresholds and value weights. This is how moral laundering becomes structural: the institution behaves as if nobody decided, even though the system’s design encoded decisions everywhere.

Governance exists to prevent that outcome. It assigns responsibility, draws authorization boundaries, makes policy-setting explicit and reviewable, and resists the slow erosion of safety

constraints through drift and incentive. In no-audit scenarios especially, governance is not a bureaucratic add-on. It is the difference between an instrument and an unaccountable actor.

12.1 Who is accountable when the system acts under uncertainty

Accountability is often framed as “who is to blame when things go wrong,” but in high-stakes systems the more important framing is “who had the authority to choose the risk profile.” Uncertainty ensures that some outcomes will be bad even when decisions are made competently. The question is whether those decisions were legitimately authorized and whether the system acted within that authorization.

A workable accountability structure separates roles, because a single person cannot realistically carry all responsibility.

Policy authority: The entity responsible for setting the normative layer—thresholds, defaults, red lines, and escalation rules. In public settings this may be a governmental or regulatory authority; in private settings it may be an accountable executive body subject to law and oversight. This authority is accountable for the moral shape of the system: which errors are treated as acceptable and which are not.

Operational authority: The entity responsible for using the system in context—operators, supervisors, and incident commanders. They are accountable for compliance with procedures, appropriate overrides, and proper escalation. They are not accountable for the system’s deep statistical properties, but they are accountable for how it is used.

Technical authority: The entity responsible for building, maintaining, and validating the system—engineers, safety teams, model auditors, and security teams. They are accountable for whether the system meets its stated performance, calibration, and safety envelope, and for whether it reliably triggers safe-mode under abnormal conditions.

Institutional authority: The organization that deploys the system and benefits from it. This authority cannot evade accountability by blaming the model, the vendor, or the operator. If the institution chose to deploy the system and to grant it authority, the institution is accountable for that decision.

This role separation prevents a common failure: scapegoating the operator after a tragedy that was structurally inevitable given system design and institutional incentives. In a healthy governance model, responsibility is layered and matched to the kind of decision being made: moral policy decisions belong to policy authority, technical competence belongs to technical authority, operational compliance belongs to operational authority, and the choice to deploy belongs to institutional authority.

In no-audit scenarios, accountability must also be explicit before deployment. The system cannot be introduced first and governed later. If nobody can say, clearly, who is responsible for a catastrophic decision pathway, then the system is not ready to be deployed.

12.2 Authorization boundaries: what the system may recommend vs what it may execute

The sharpest governance question is not "is the system accurate," but "what is the system allowed to do." This is where the two-layer architecture becomes operational: epistemic outputs inform, normative boundaries constrain.

Authorization boundaries should be specified along at least four axes.

Action tier boundaries: Which tiers of action the system may execute autonomously. In most high-stakes domains, autonomy should be limited to reversible and bounded interventions: alerting, friction, rate limiting, containment, and safe-stop. Irreversible actions should be prohibited or require explicit human confirmation plus multi-party approval.

Domain boundaries: What contexts the system is allowed to operate in. A system validated for one environment should not silently expand into another. "Works in the lab" is not authorization for "works in the field."

Condition boundaries: What the system may do under abnormal conditions. Distribution shift, sensor degradation, disagreement among redundant systems—these should trigger authority contraction. Under such conditions, the system's permission set should shrink automatically.

Escalation boundaries: When the system must hand off or seek confirmation. Escalation rules are not optional; they are the mechanism that keeps legitimacy attached to decisions that depend on contested values.

The difference between recommendation and execution is also crucial. A system that recommends can be wrong and still be useful, because humans can apply context, values, and accountability. A system that executes has already crossed into the exercise of power. In some domains, execution must remain human by design, because the legitimacy of the act depends on accountable human agency.

These boundaries must be concrete, not aspirational. They must be encoded in access controls, technical gating, and circuit breakers. If boundaries exist only in policy documents, operational pressure will erode them. If boundaries exist in system architecture, they can resist pressure.

12.3 Policy-setting as a public act: thresholds, red lines, and review cadence

Thresholds and defaults are moral decisions. Red lines are moral decisions. Safe-mode triggers are moral decisions. Even the choice of what metrics to optimize is a moral decision because it determines who bears error.

Therefore policy-setting must be treated as a public act in the relevant sense of "public." In democratic contexts, that may be literal public governance: laws, regulations, hearings, and judicial oversight. In organizational contexts, it may be internal transparency to stakeholders, clear documentation, independent review, and meaningful appeal mechanisms. The point is that the value choices embedded in the system should not be hidden in technical parameters.

A credible policy-setting process includes:

Explicit thresholds and their rationale: Not just the number, but why that number reflects the acceptable balance of false positives and false negatives for the domain, especially near irreversible boundaries.

Explicit red lines and escalation requirements: Clear statements about what the system must never do autonomously, and what requires multi-party approval, out-of-band confirmation, or legal authorization.

Review cadence and revision triggers: Policies must be revisited on a regular schedule and also when certain events occur: drift indicators, near-misses, red-team discoveries, major distribution shifts, or changes in law and norms.

Versioning and change control: When thresholds change, the change should be tracked, justified, and attributable. Quiet threshold creep is one of the most common pathways to safety erosion.

Public reasoning artifacts: In high-stakes deployments, there should be a standardized explanation of the system's authorization boundaries and safety posture that stakeholders can understand. This does not require revealing sensitive technical details. It requires clarity about what the system is allowed to do and what recourse exists when it harms someone.

Treating policy-setting as public is not merely ethical. It is practical. Hidden thresholds become liabilities. When harm occurs, the institution will face crisis not only because harm happened, but because harm happened under secret rules. Transparency of policy is therefore part of legitimacy preservation.

12.4 Preventing normalization of deviance: drift, quiet redefinitions, and metric capture

Even well-governed systems degrade over time. The most dangerous degradation is not sudden failure; it is normalization of deviance: the gradual acceptance of behaviors that would once have been considered unsafe, because they become routine and appear to work.

This happens through several pathways.

Drift: The environment changes, model calibration erodes, and safe-mode triggers become more frequent. Instead of treating this as a warning, organizations may "fix" the annoyance by

widening thresholds, suppressing safe-mode, or reducing escalation. The system becomes smoother and more dangerous at the same time.

Quiet redefinitions: Words like “urgent,” “credible,” “high risk,” and “safe” shift meaning over time. What once required human confirmation becomes “automated for efficiency.” What once counted as a red line becomes “rare exception.” The governance boundary erodes without a formal decision to erode it.

Metric capture: The system’s success becomes defined by a proxy metric that is easy to track, and the proxy gradually displaces the real value. For example, reducing incident reports becomes the goal rather than reducing real harm; increasing interdictions becomes the goal rather than increasing justice; reducing downtime becomes the goal rather than preventing catastrophic failure. Once capture occurs, the system may look “successful” while becoming morally worse.

Override culture: If operators override safety constraints frequently, the constraints become decorative. Conversely, if operators never override, it may indicate automation bias and silent deference. Both extremes can be dangerous. Governance must monitor override patterns and treat them as signals of system-health and institutional incentives.

To prevent normalization of deviance, governance must be continuous and structural.

First, monitor safety posture metrics, not just performance metrics. Track safe-mode frequency, disagreement rates among redundant systems, threshold crossing rates, override rates, and time-in-degraded modes. Sudden changes in these often precede disaster.

Second, enforce change control. Any change to thresholds, defaults, or red lines should require documented justification and independent review. The goal is to make drift visible and to force explicit choices rather than silent slide.

Third, institutionalize independent veto power. A safety office or external auditor must have the authority to halt deployment, shrink envelopes, or require retraining when drift is detected. Independence matters: without it, safety concerns will lose to operational pressure.

Fourth, preserve appeal and recourse. Systems that harm people will generate backlash. If there is no meaningful appeal, institutions will be tempted to suppress evidence of harm rather than address it. Appeal mechanisms therefore protect both individuals and system legitimacy.

Fifth, rehearse failure modes. Organizations should practice what happens when the system refuses to act, when it enters safe-mode, when it triggers circuit breakers. If safe-mode is treated as crisis, it will be optimized away. If safe-mode is treated as success under uncertainty, it will survive.

The overall thesis of governance is straightforward: the technical system cannot preserve legitimacy by itself. Legitimacy is preserved by making authority explicit, binding it to accountable agents, and preventing the slow erosion of safety boundaries under incentive and habit. In the AGI era, the core danger is not only that models will be wrong. It is that institutions will quietly grant them more authority than anyone would openly defend. Governance exists to keep that from happening.

13. Implementation Blueprint: A Practical Design Pattern for Judgment Calls

The purpose of this blueprint is to translate the paper's moral claims into an implementable pattern: a repeatable way to build systems that make judgment calls without becoming unaccountable moral actors. The blueprint does not assume perfect prediction, perfect explainability, or perfect oversight. It assumes fallibility, pressure, novelty, and drift—and then designs for survivability.

A practical design pattern for judgment calls has five steps. First, classify actions by reversibility and blast radius. Second, pick a default posture that minimizes regret for each class, including an operationally real abstention/safe-mode option. Third, configure thresholds and gates so that higher-commitment actions require stronger evidence and stronger authorization. Fourth, monitor continuously for shift and abnormal conditions, with circuit breakers that contract authority. Fifth, deploy with discipline: staged rollouts, fail-safes, and rollback pathways so the system can be safely corrected.

The key idea is that the system is not "one model deciding." It is a governed pipeline that moves from inference to action through explicit constraints.

13.1 Decision taxonomy: classify actions by reversibility and blast radius

You cannot govern what you have not named. The first step is to build a decision taxonomy that classifies every action the system might take. This taxonomy becomes the basis for permissions, thresholds, and safe-mode behavior.

At minimum, classify actions along two axes.

Reversibility: If the action is wrong, can it be undone or compensated? Reversibility is not binary. It includes degrees:

- fully reversible (a warning, a temporary delay, a query for confirmation)
- reversibly contained (temporary isolation of a subsystem)
- reversible but costly (temporary hold that causes significant inconvenience)

- partially irreversible (actions that can be undone but not fully repaired, such as reputational harm)
- fully irreversible (lethal force, permanent deprivation, irreversible medical procedures, strategic escalation)

Blast radius: If the action is wrong, how many people or systems are affected, and how broadly can harm cascade? Blast radius can be:

- local (one user, one component)
- regional (a facility, a network segment)
- systemic (an entire organization or infrastructure)
- strategic (international or existential consequences)

With these axes, you can build a grid of action classes, and then assign policies to each class. For example:

- Class A: reversible + local
- Class B: reversible + systemic
- Class C: partially irreversible + local
- Class D: partially irreversible + systemic
- Class E: irreversible + local
- Class F: irreversible + systemic/strategic

The classification must be grounded in domain reality. A “temporary” action can be effectively irreversible if it triggers cascade, destroys trust, or causes life-threatening delay. Therefore blast radius and time sensitivity must be included in classification, not treated as afterthoughts.

The practical output of this step is a table of actions with their class, their required authorization, their minimum confidence requirements, and their safe-mode alternatives. This table becomes the normative layer’s core artifact.

13.2 Default-action selection: choose the least-regret posture per class

Once actions are classified, the next step is to define default postures under uncertainty for each class. Defaults matter because uncertainty is the normal condition, not the exception. If defaults are implicit, organizational incentives will select them by drift.

“Least-regret posture” means: choose the default that minimizes catastrophic downside if the system is wrong. This is not simply “be conservative.” It is domain- and class-specific.

For reversible-local actions, act-by-default may be acceptable: warn, request verification, slow down, gather more data. The regret of a false positive is small and reversible.

For reversible-systemic actions, safe-mode-by-default is often better: contain and rate-limit rather than broadly intervene. Even reversible actions can have large collateral when systemic.

For partially irreversible actions, deny-by-default or escalate-by-default is appropriate. If an action can cause lasting harm even if reversed later, the system should not take it autonomously under ambiguity. It should choose a lower tier and escalate.

For irreversible actions, the default should be prohibition or strict gating. If the system cannot satisfy multi-layer authorization, it must not act. Its default is to stabilize, contain, and hand off, even if that feels “inefficient.”

Default selection should also define what abstention means operationally. Abstention is not silence. It is a safe-mode posture: slow, isolate, degrade, rate-limit, and handoff in ways appropriate to the class.

A strong discipline here is to explicitly define “safe-mode analogs” for every high-impact action. If the system is tempted toward a high tier, it must have a pre-defined lower-tier move that buys time and reduces harm. If no such move exists, the system is structurally unsafe because it forces cliff-edge choices.

13.3 Threshold and gating configuration: from single-step to multi-tier pipelines

With action classes and defaults defined, thresholds and gating can be configured as an explicit pipeline from inference to execution.

A useful pattern is to define three kinds of thresholds:

Epistemic thresholds: confidence and reliability requirements. These include calibrated probability, uncertainty bounds, and shift signals. Epistemic thresholds determine whether the system is allowed to consider certain actions at all.

Normative thresholds: policy gates based on values and constraints. These are not probabilities. They are permissions: which actions are allowed, which require confirmation, which are forbidden, and which require multi-party approval.

Operational thresholds: system-health conditions. These include sensor integrity, logging availability, redundancy agreement, and communication status. If operational thresholds are not met, the system’s authority contracts regardless of confidence.

A single-step pipeline is appropriate only for the lowest action tiers. For example, “issue alert” may be triggered by a modest confidence threshold with minimal gating.

For higher tiers, the pipeline must be multi-tier:

Tiered action pipeline example:

- Stage 1: detect and score (epistemic)
- Stage 2: choose among reversible actions (normative + operational checks)
- Stage 3: if a stronger action is considered, require redundancy agreement (multi-system)
- Stage 4: require out-of-band confirmation (separate channel)
- Stage 5: require multi-party human approval (two-person rule)
- Stage 6: execute with bounded envelope and time limits

Each stage has explicit failure behavior: if the stage cannot be satisfied, the system falls back to safe-mode or a lower tier. It does not “do its best anyway.” That is the moral difference between governed autonomy and uncontrolled automation.

The configuration should also include veto logic: a single credible dissent from an independent system should block movement into irreversible tiers. Disagreement is not noise at the boundary; it is the signal that the world is ambiguous or compromised.

Finally, thresholds should be versioned and protected. If thresholds can be quietly changed in production to reduce safe-mode events, then governance has already failed.

13.4 Monitoring: shift detection, circuit breakers, and continuous validation

A judgment system is not “deployed and done.” It lives in a changing world. Monitoring is therefore not a dashboard; it is an active safety system whose job is to detect when the system’s authority must shrink.

Monitoring must include at least four classes of signals.

Shift detection: indicators that inputs are outside the training regime. This includes statistical drift, novelty detection, changes in sensor distributions, and changes in population base rates. Shift signals should increase uncertainty and expand safe-mode.

Disagreement and consistency checks: measure how often redundant systems disagree, how often internal consistency constraints are violated, and how often reason packets show unusual feature reliance. Rising disagreement is an early warning that the system is near its limits.

Circuit breaker triggers: predefined conditions that automatically constrain action. For instance:

- high uncertainty combined with high action tier request
- repeated near-threshold triggers (instability)
- missing logs or inability to produce reason packets
- loss of supervisory communication
- sensor anomalies that suggest spoofing or failure
  When breakers trip, the system contracts authority, rate-limits actions, and escalates.

Continuous validation: periodic and event-triggered evaluation against scenario suites, near-miss data, and red-team probes. This is where auditability supports safety without relying on catastrophe. The system must be measured regularly for calibration, safe-mode behavior, override patterns, and compliance with authorization boundaries.

A critical monitoring metric is “authority creep.” If over time the system executes higher tiers more often, enters safe-mode less often, or receives more overrides that expand action, governance should treat this as a safety regression unless it is explicitly justified by improved validation evidence.

Monitoring also must be resilient. If monitoring fails, the system should not continue at full autonomy. Monitoring loss is itself an abnormal condition: it should trigger a dead-man style contraction of authority.

13.5 Deployment discipline: staged rollout, fail-safes, and rollback procedures

Even a well-designed system will be wrong in unexpected ways. Deployment discipline is the practice of making wrongness survivable.

Staged rollout means granting authority gradually:

- start in shadow mode (recommendations only, no execution)
- then allow reversible-local actions within tight envelopes
- then expand reversible actions slowly, measuring drift and harm
- only consider higher tiers if evidence and governance justify it

At each stage, define success criteria that include safety posture, not just performance. For example: acceptable calibration error, acceptable safe-mode frequency, acceptable disagreement rates, acceptable operator override patterns, and absence of catastrophic pathway vulnerabilities in red-team tests.

Fail-safes must be real and tested. A fail-safe is not a document; it is an operational capability:

- manual override that reliably returns the system to a safe posture
- fallback controllers for time-critical domains
- automatic safe-mode on monitoring loss
- rate limits that cannot be disabled casually
- hard prohibitions on irreversible actions without required gates

Rollback procedures are essential because model updates can introduce new failure modes. Every deployment should have:

- version control of models and thresholds
- the ability to revert quickly to a known safe version
- a clear decision authority for rollback
- rehearsed rollback drills, not theoretical plans

Finally, deployment discipline must include institutional incentives. If leadership punishes safe-mode events as "downtime," engineers will tune them away. If operators are rewarded only for throughput, they will override constraints. Therefore deployment discipline is partly a cultural governance artifact: safety posture must be treated as success, not as friction to be optimized away.

This blueprint completes the paper's move from philosophy to practice. It offers a repeatable design pattern: classify actions, define least-regret defaults, build multi-tier gating pipelines, monitor for drift with circuit breakers that contract authority, and deploy in staged, reversible steps with fail-safes and rollback. The result is a system that can assist with judgment calls at speed without becoming a single-point agent of irreversible harm.

14. Conclusion: Reframing Judgment as Architecture

The paper began with an ordinary human phrase—"judgment call"—and treated it as a serious engineering problem. Humans say "judgment call" when evidence is incomplete, outcomes are uncertain, values are in tension, and a decision must be made anyway. That problem does not disappear in the presence of AGI. It sharpens. Speed increases. Scale increases. Delegation becomes tempting. And in some situations there will be nothing left to audit if the system is wrong.

The conclusion is not that judgment is impossible for machines, nor that machines should never act. The conclusion is that judgment cannot be solved by intelligence alone. It must be solved by architecture: by designing systems that treat uncertainty as normal, make abstention operational, privilege reversibility-first actions, gate irreversible decisions behind multi-layer authority, and contract autonomy when conditions become abnormal. In this frame, the decisive question is not "can AGI make the right call," but "can we build systems in which wrong calls do not become irreversible catastrophes."

14.1 The core synthesis: uncertainty is inevitable, catastrophe is optional

Uncertainty is a permanent feature of the world. Sensors are imperfect. Data is partial. Adversaries exist. Distribution shifts. Human goals are contested and sometimes contradictory. Any system that acts in the world must act without full knowledge. That is not a failure of modeling; it is the condition of being embedded in reality.

What is optional is catastrophe. Catastrophe is not simply "being wrong." Catastrophe happens when wrongness is allowed to propagate into irreversible harm without barriers. It is a structural event: a failure of gating, of defaults, of escalation, of redundancy, of safe-mode. Put differently, catastrophic outcomes are often not proof that the system was unintelligent. They are proof that the system was authorized to act as if it were infallible.

This is why the paper's focus has been on the path from inference to action. Inference will sometimes be wrong. The ethical question is what happens next. If the design routes uncertainty into reversible stabilization and escalation, then wrongness becomes survivable and learnable. If the design routes uncertain inference into decisive irreversible action, then wrongness becomes tragedy.

The synthesis can be stated cleanly: build for the world as it is. Assume uncertainty. Assume drift. Assume pressure. Then design the action pipeline so that uncertainty triggers containment rather than escalation, and so that no single inference can cross a catastrophic boundary. This is not pessimism. It is realism with compassion: a refusal to gamble lives on calibration.

14.2 Why the safest AGI is constrained, layered, and permission-aware

If intelligence is not enough, what is enough? The answer is not "more caution" in the abstract. It is three concrete properties that together create safety without requiring trust at the boundary.

Constrained: The system's action space is limited by design. It is not allowed to execute irreversible actions solely from its own inferences. Its permissions are tied to tiers, to reversibility classes, to blast radius constraints, and to explicit policy gates. Constraint is not weakness; it is the mechanism that keeps power from becoming illegitimate.

Layered: The system's decision pathway has multiple stages and multiple barriers. Low-stakes reversible actions can be fast. High-stakes actions require stronger evidence, redundancy agreement, out-of-band confirmation, and often multi-party human authorization. Layering makes safety robust to component failure because it prevents single-point agency.

Permission-aware: The system does not confuse probability with permission. It can estimate likelihood, but permission comes from a normative layer that encodes thresholds, defaults, red lines, and escalation rules set by legitimate authority. Permission-awareness prevents moral laundering: the system cannot pretend that value choices are facts.

These properties are what make safe-mode meaningful. Safe-mode is not an apology; it is a designed behavior that buys time, reduces collateral, and preserves options. A permission-aware system is willing to abstain because it knows abstention is allowed. A layered system can hand off because escalation pathways exist. A constrained system remains useful because it has powerful reversible tools even when it cannot act decisively.

This also clarifies why "explainability" is supportive but not primary. Explanations can help oversight and learning, but only constraints can prevent irreversible harm when the system is wrong. The safest AGI is therefore not the most persuasive or the most confident. It is the one that behaves predictably under uncertainty, refuses unauthorized escalation, and contracts authority when its own reliability is in question.

In practical terms, this is a reframing of what it means for AGI to be "aligned." Alignment is not a property of the model's internal beliefs. It is a property of the socio-technical system: the gates, the permissions, the defaults, the monitoring, and the human institutions that remain accountable for values.

14.3 Future work: formal guarantees, domain standards, and audit-independent safety culture

This paper has argued for architectural discipline, but the work ahead is to turn discipline into standards and, where possible, guarantees.

Formal guarantees: Some safety properties can be formalized. For instance, one can specify that certain action tiers are unreachable without multi-party approval, that circuit breakers must trip under defined abnormal conditions, or that authority must contract under detected shift. Formal methods cannot capture all ethical nuance, but they can lock in critical invariants: "no direct path from single inference to catastrophic act," "safe-mode is always available," "irreversible actions require explicit gates."

Domain standards: Each domain needs its own concrete safety envelope definitions. Autonomous vehicles need validated safe-stop behaviors, bounded maneuver sets, and

conservative fallback controllers. Medical systems need protocols that distinguish reversible stabilization from irreversible intervention and keep final authority with clinicians. Security and fraud systems need tiered responses with meaningful appeal and transparency about thresholds. Strategic contexts require explicit prohibitions and multi-layer authorization for escalation. Standards should specify not only model performance metrics but governance metrics: safe-mode rates, disagreement rates, override patterns, and evidence of authority contraction under novelty.

Audit-independent safety culture: Perhaps the most important future work is institutional. A culture that treats post-mortems as the primary safety plan will eventually discover the boundary where post-mortems are impossible. The needed culture treats near misses as primary data, safe-mode as success, and friction at irreversible boundaries as a moral requirement. It resists the pressure to optimize away constraints for throughput. It insists that value choices be made openly, and that responsibility remain attached to accountable agents.

The practical hope is not that we will eliminate error. It is that we will eliminate the class of failures where error becomes irrecoverable because the system was allowed to act as if it were beyond error. When the world forces a judgment call, the question is not whether the machine can "be wise." The question is whether the architecture can keep us within the space of reversible moves long enough for legitimate authority—human and accountable—to decide what must be done.

The paper's final claim is therefore a modest but demanding one: uncertainty is inevitable, but catastrophe is optional—if we build systems whose permissions are explicit, whose autonomy is layered, and whose first move is almost never their last move.

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The author has published over 4,800 AI-assisted papers at: https://www.researchgate.net/profile/Douglas-Youvan/research . Google Scholar has indexed these preprints, and if you want a particular reference, the AI mode of a Google search (Gemini) has efficiently catalogued these preprints.